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The good tourist, the bad refugee and the ugly German: Xenophobic activities and tourism

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Abstract

This article deals with the economic effects of xenophobic incidents. To analyze these effects, we focus on one important industry, namely tourism. Combining a novel, district-level data set on tourism in Germany with data on xenophobic activities, we find that xenophobic demonstrations lead to a decline in tourism numbers. A media analysis on German newspapers shows that the effect is driven by the media attention towards the incidents. Looking at Dresden as a case study with the Synthetic Control Method provides support for our results. The findings presented here highlight the direct economic costs of xenophobia and strengthen the political case to fight political extremism.

Keywords: Xenophobia, refugees, tourism, district-level data

JEL Classification: F22, L83

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1 Introduction

The increasing political polarization all around the world is a key feature of the 21st century. In many countries, this development goes hand in hand with xenophobic sentiments. Xenophobia has been studied from many perspectives, but its economic costs are unclear. In this article, we use empirical data from Germany to highlight one direct economic cost of xenophobia, its effect on tourism.

The large influx of refugees to Germany since the beginning of the Syrian civil war in 2011 has led to the rise of a new right-wing party and xenophobic demonstrations and attacks. While these events have had a large impact on Germany's political and social landscape, we investigate the economic effects of these reactions to refugees. Xenophobic activities, such as the violent demonstrations in Chemnitz in August 2018, receive coverage in the (international) media and put the location in a negative spotlight. For the local economy, this image can have economic repercussions.

This research is, to our knowledge, the first that deals with the direct economic effects of xenophobic activities. Tourism plays an important role in the economy of developed and developing countries (Faber and Gaubert, 2019). In Germany, it accounts for almost 5 percent of the overall economic activity (German Travel Association, 2015). We construct a novel district-level data set on tourism in Germany to analyze the effects of xenophobic activities¹ on local tourism. The data is available at within-year frequency and we aggregate it at the quarterly level to measure the short-term effects of the incidents. Analysing the relationship at the sub-national level comes with the advantage of using the variation of tourism across districts while holding factors constant that affect tourism flows on the national level. Our outcome of interest is the growth rate of tourism over time and we control for different growth paths and country-level shocks. The empirical analysis accounts for alternative explanations such as cultural events, economic conditions or meteorological features.

We find that xenophobic demonstrations reduce tourism growth in subsequent quarters. The effect is strongest in the two periods after the incident, while we can observe a partial reversion of the effect after four periods. These results are in line with our expectations that tourists take time to respond to an incident and that the effect of incidents further in the past fades away. It is

¹As used in this article, these include physical attacks, arson, demonstrations and miscellaneous attacks against refugee housing.

significant for both the absolute number and the per capita number of xenophobic incidents and is relevant for both domestic and foreign tourists. We observe that a reduction in the absolute number of visiting tourists drives the change rather than a shorter duration of the visit.

To provide evidence on the transmission channel from incidents to tourist reactions, we extend our analysis to the media attention that xenophobic incidents receive. We collect reports that cover xenophobic incidents from the main national German newspapers and create an indicator that captures media attention on xenophobia per quarter for each district. We first show that media attention on xenophobia in a district increases after xenophobic incidents in the vicinity, with the strongest effect for xenophobic demonstrations. Second, we observe that media attention reduces tourism growth in the district in the two quarters after the report. This effect is temporary and tourism numbers recover after one year.

To illustrate the effect of xenophobic incidents on the attractiveness of a city, we also use a synthetic-control approach. Dresden as a district with a high-profile anti-refugee movement, Pegida, serves as the exemplary case of a destination that was affected by many xenophobic incidents. We show that the xenophobic demonstrations have led to a significant reduction in tourism growth in Dresden.

This article is an addition to the literature on the economics of hate crimes. While the existing literature is concerned with determinants, we focus on the economic effects of xenophobic activities. The finding of media coverage as the transmission channel adds to a literature that evaluates how media affects the preferences and behavior of individuals (Dahl and DellaVigna (2009), DellaVigna and Kaplan (2007), Eisensee and Strömberg (2007)). The next section will review the relevant literature, while section 3 presents the theoretical considerations behind our analysis. Section 4 is the core section of our article. We discuss our baseline model, present an extension focusing on media attention given to xenophobic activities and use a synthetic-control approach to provide further evidence for our results. A final section concludes.

2 Literature Review

The literature on xenophobic activities has been focused on understanding the determinants of those activities for the past two decades. One of the first contri-

butions to the literature was (Gale et al., 2002). Their most interesting finding is that a narrowing income gap between black and white people is increasing hate crimes of whites against black. They interpret the finding as a result of envy. Sharma (2015) finds a similar result when looking at caste differences in India and the corresponding hate crimes against people from a low caste. More straightforward is the finding that right wing violence occurs more often in times of high unemployment (Falk et al., 2011).

Another debate in the literature looked at the role of hate groups, such as the Ku Klux Klan. Ryan and Leeson (2011) and Mulholland (2013) both analyze the effect of hate groups on hate crimes. Ryan and Leeson (2011) find no significant effect of hate groups on hate crime. Mulholland criticizes this result and finds, using methodological improvements, that counties with a white supremacist hate group are around 20% more likely to experience a hate crime. To sum up, the results strengthen the conventional wisdom that hate groups are determinants of hate crime.

Cultural factors can play an important role. Xenophobic activities are more likely when the cultural distance between the migrants and the local population is large (Tabellini, 2019) and when an influx of foreigners leads to a rapid compositional change in the population (Entorf and Lange, 2019). But violence against migrants is mitigated when government efficiency is high and integration is well organised (Ziller and Goodman, 2020). Researchers have discussed the role of social media as a determinant of xenophobic activities (Muller and Schwarz (2018), Bursztyn et al. (2019)). Their main finding in a nutshell is that a higher penetration of social media and more right-wing social media users lead to more attacks on foreigners.

While these results elaborate on the determinants of xenophobic activities, the literature on the consequences of xenophobic activities is less developed. Only in recent years, researchers have paid closer attention to the effects. Steinhart (2018) studies the attacks on Turkish immigrants in the early 90s in Solingen and Moelln. He detects a reduction in subjective well-being for citizens with a Turkish background and an increased intention to return home. Investment in integration such as language skills are reduced.

In a similar vein, Gould and Klor (2016) use the backlash of hate crimes against Muslim immigrants after 9/11 to show that xenophobic activities hinder assimilation. An increase in the anti-muslim hate crimes lead to more inter-ethnic marriages, higher fertility, lower female labor market participation and lower English language proficiency. Hole and Ratcliffe (2020) look at the well-

being of muslim adolescents around the London bombings in 2005 and find that the more hostile environment after the extremist Islamic terror attack negatively affected teenage girls, who also reported a rise in the expected discrimination on the labor market. Anti-muslim hostility can also result in radicalization on the side of the victims and increase the support for muslim terror groups (Mitts, 2019). Friebel et al. (2013) use an outburst of violence in South Africa to test how it affects the intentions to migrate from neighboring sending countries. They show that xenophobic activities in the recipient country reduce the intention to migrate.

These contributions focus on indirect costs of xenophobic activities (such as integration and migration). Xenophobic attacks affect the preferences and behavior of the target groups, in our examples muslim minorities. But the incidents can have an effect on the behavior of other observers as well. Tourists are one group of observers that play an important role in an economy. Understanding their reaction tells us about direct costs of xenophobic violence.

There has been some research on the effect of extreme political situations on tourism. Neumayer (2004) was the first to look at the effect of political violence on tourism. For terrorist events, conflict events and human rights violations, he finds that political violence reduces tourist arrivals. Saha and Yap (2014) look deeper into the relationship of political instability and terrorism and their joint effect on tourist arrivals. They find that political instability has a detrimental effect for all levels of terrorism. Ahlfeldt et al. (2015) look more closely at the shifts in tourism demand from terrorist attacks. They can show that, besides geographic proximity, ethnic-religious proximity plays a big role for the effect of terrorist attacks. The attacks of 9/11 and other Islamic attacks reduced tourism demand in the affected countries, but also in unaffected, Muslim-majority countries.

Altogether, our paper is a novel addition to the growing literature on the effects of xenophobic activities by taking a focus on the effects on tourism, while we *vice versa* add to the literature analyzing the determinants of tourism by adding xenophobic activities to the picture.

3 Theory

Prices for accommodation, general holiday expenditures (including grocery prices, costs for restaurant visits and entrance fees for museums and other tourist at-

tractions) and travel costs form the direct, monetary part of the choice of a tourism destination. These factors can be analyzed with standard economic models. But, there is little economic theory on the underlying mechanisms of the attractiveness of a tourism destination. This attractiveness is driven by a multitude of factors, including geographic features such as beaches, mountains or lakes; the availability of tourist attractions such as amusement parks, UNESCO world heritage sites or skiing resorts or important sports events like World championships. Neumayer (2004) shows that political violence, such as terrorist events or human rights violations, can reduce the attractiveness of a tourism destination. We hypothesize that a higher level of xenophobic activities is another factor that impacts the general attractiveness of a location for tourists.

We argue that destinations which experience larger amounts of xenophobic activities will receive a discount in attractiveness compared to other destinations with similar features but a lower level of xenophobic activities.

Hypothesis 1a: A higher level of xenophobic activities has a negative impact on tourism.

We expect that the reduction in attractiveness has an effect on the external margin, the number of tourist arrivals, but no direct effect on the internal margin, the average duration of the stay. The underlying argument is that while aspects such as number of days off from work or financial constraints affect the duration of the stay, the choice of destination is also driven by the attractiveness, which is reduced by xenophobic activities. But if xenophobic activities result in a reduction in demand for vacation accommodation, hotels might be intrigued to lower their prices. According to revenue management models hotels continuously optimize their pricing strategy depending on forecasted demand. Evidence exists that dynamic pricing based on the number of rooms sold in the hotel industry is prevalent (Lewis and Zervas, 2019). With price decreases, we would expect visitors to increase the duration of their stay.

Hypothesis 1b: A higher level of xenophobic activities reduces tourist arrivals.

Hypothesis 1c: A higher level of xenophobic activities increases the average duration of the stay.

A second influence on the decision of tourists, besides the reduction in attractiveness, is the effect on (perceived) safety levels. This influence should be more pronounced for foreigners than for domestic tourists. The foreign tourist is concerned that she could become the victim of a xenophobic attack.

Hypothesis 2: A higher level of xenophobic activities has a stronger negative impact on foreign tourists compared to domestic tourists.

From a theoretical point of view, this effect should be stronger for foreigners with distinct physical differences, e.g. in skin color, to German nationals. For this paper, the data does not allow for a comprehensive analysis of tourist characteristics in terms of outer appearance, so we cannot test this conjecture.

The arguments presented above rely on the fact that potential tourists are aware of xenophobic activities. Since information acquisition is costly, it is unlikely that tourists are aware of all xenophobic activities. We hypothesize that media attention is a key transmission channel for the above-mentioned effects of xenophobic violence on tourism.

Hypothesis 3: An increase in xenophobic activities leads to more media reports on xenophobia.

Hypothesis 4: A larger number of media reports on xenophobic activities has a negative impact for tourist arrivals.

4 Empirics

4.1 Baseline Model

4.1.1 Data and empirical specifications

For our analysis of the short-term impact of xenophobic activities on tourism, we focus on the development of tourism in Germany from 2014 to 2017. This period coincides with the so-called refugee crisis. We got access to information on tourism numbers from the statistical offices of the German states and created a dataset on tourism for 401 German districts from 2012 until 2017.

German districts are an administrative level in between the German states and the municipalities and consist of 294 rural districts (Landkreise) and 107 urban districts (Kreisfreie Staedte). They fulfill policy tasks including education, public transportation and the development of local tourism.

Most of the tourism industry is organized at the local level. Marketing activities and investment into tourism infrastructure are decided locally. As visitors also base their decision on characteristics of the destination, it is useful to analyse xenophobic costs for tourism at a low administrative level. The tourism data is available on a monthly basis and includes information on the number of overnight stays, the number of visitors who spent at least one night in a guest facility and the average duration of stay. For each category, the data allows us to distinguish between domestic and foreign visitors based on their residence.² The guest facilities report the numbers³ and we aggregate the data at the quarterly level.⁴ The aggregation helps to lower the large very short-term fluctuations and potential measurement error from misreporting of tourism numbers by hotels. We end up with 399 counties in our sample as Günzburg and Mayen-Koblenz drop out due to measurement errors in their tourism data.

Tourism numbers in Germany have been rising between 2014 and 2017, with a 10.46 percent increase for foreign visitors and a 7.54 percent increase for domestic tourists in terms of overnight stays. Figure A1 shows the development over time and reveals the strong seasonality. Tourism demand is lowest in the fourth quarter, the winter period, and the highest in second quarter, the summer. In Figure 1 we see the uneven distribution of the growth rate in tourism across counties, ranging from a loss of tourists of 28 percent for the county Kusel to an increase of 81 percent for the county Haßberge. Our interest is if xenophobic incidents can explain part of this variation in tourism development across Germany.

We relate the development in tourism to incidents of anti-refugee incidents in the districts. The NGOs Amadeu Antonio Stiftung and Pro Asyl offer a repository on violence and social unrest aimed at refugees. The activities are categorized into xenophobic demonstrations, assault, arson attacks and miscellaneous attacks against refugee housing, and include information on the timing

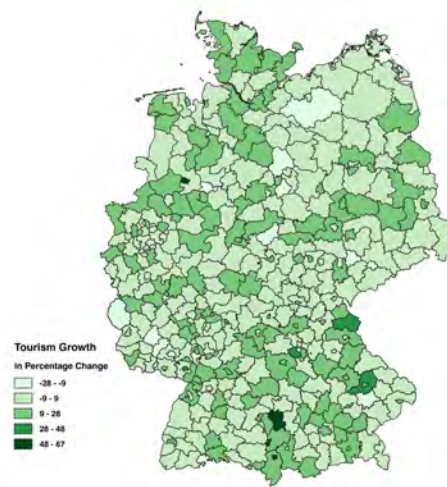
²The origin is related to the country of residence

³The law requires all hotels and camping sites with more than 10 beds to report the numbers to the public authorities.

⁴We define Quarters as January to March, April to June, July to September, and October to December.

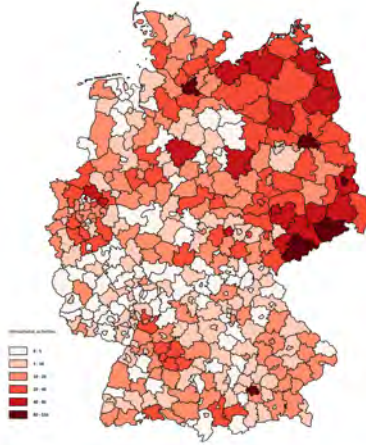
and the location of the events. We extend the dataset by Benček and Strasheim (2016) to the end of 2017 and aggregate it at the quarterly level per district. Our sample entails 4715 cases of miscellaneous attacks, 968 cases of assaults, 272 cases of arson and 423 demonstrations. Figure 1 shows the spatial distribution of the activities by district. Darker shaded areas saw more xenophobic activities.

Figure 1: Cases of xenophobic activity



The figure shows the percentage change in overnight stays per district between 2014 and 2017. Darker shaded areas experienced stronger growth.

Figure 2: Cases of xenophobic activity



The figure shows the number of aggregated xenophobic activities per district. Darker shaded areas experienced more xenophobic activities.

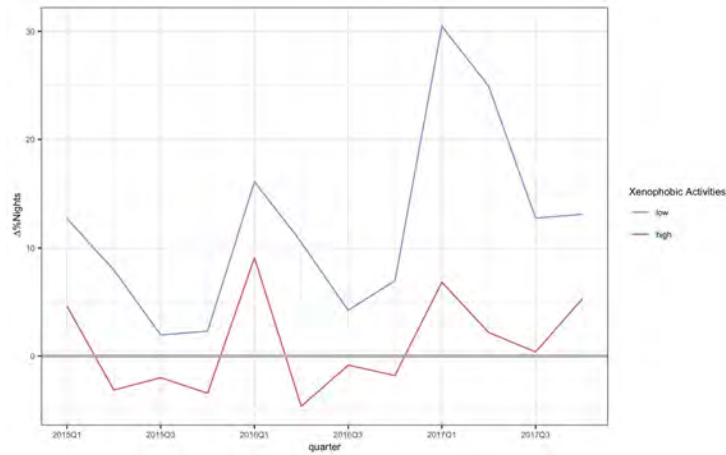
Xenophobic activities were at a low level in the beginning in 2014, but numbers increased towards the year 2015 (see A2). The peak in the overall number of incidents was around the first quarter of 2016. Afterwards, miscellaneous attacks, arson attacks and demonstrations decreased, while assaults remained on a high level until 2017. We will use both the absolute number of incidents per county and the normalized numbers by population in our analysis. Both cover relevant criteria when tourists decide on a destination. A (potential) tourist might perceive the danger levels of a locality based on the absolute number of incidents or on a normalized measurement. The moral assessment can depend on the absolute or relative numbers of hate crimes. A per capita measurement is more useful if for large cities other newsworthy events overshadow the attention towards an incident, while for small cities it dominates the news.

We start our examination by looking at descriptive evidence on the effect of xenophobic incidents on tourism. For this venture, it is useful to look first at the extreme cases of xenophobic incidents.

Figure 3 shows the percentage change in overnight stays for the 5 districts with the highest per capita number of xenophobic incidents, high, and the group of 5 districts who exhibit the lowest per capita number of incidents, low. With the quarters of 2014 as the baseline, the growth in tourism in the low districts

was above the high districts, and the difference in the growth rate between the two groups increased over time.

Figure 3: High and low violence districts and tourist stays

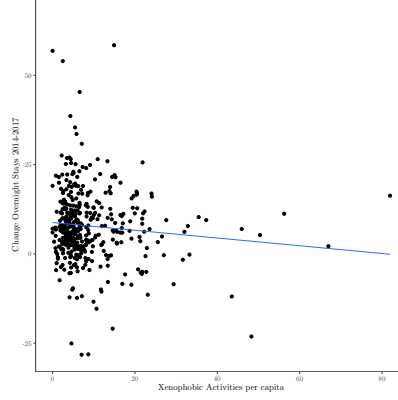


Low xenophobic: Grafschaft Bentheim, Weiden in der Oberpfalz, Coburg, Memmingen, Gross-Gerau, high xenophobic: Cottbus, Saechsische Schweiz, Uckermark, Ostprignitz-Ruppin, Frankfurt (Oder)

Then, we observe the relationship between the per capita number of incidents for each county and the change in overnight stays between 2014 and 2017. Figure 4 suggests that counties that show a larger degree of xenophobic incidents appear to experience a worse development in tourism. A negative and significant correlation coefficient between the number of incidents and the growth rate of tourism underlines the finding (see Table 1). Looking at each category of incidents, we detect a significant negative correlation for assaults, arson attacks and demonstrations.

The descriptive evidence indicates a negative effect of xenophobic incidents on tourism. But we are interested in causality, and a simple correlation with the average growth rate could mask short-term variations in the reaction of tourists or other confounding factors.

Figure 4: Correlation Cases per capita and Tourism Development



Correlation

Table 1: Correlations

Xenophobic Incidents	Incidents pc on Tourism Development
All Cases	-0.098**
Miscellaneous	-0.064
Assault	-0.0832*
Arson	-0.1655***
Demonstration	-0.150***

Note: Percentage Change in Tourism between 2014 and 2017. Pearson correlation test,
 *p<0.1; **p<0.05; ***p<0.01

To corroborate the preliminary evidence, we test whether the varying levels of anti-refugee xenophobic activities can explain the differences in tourism development.

To do this, we estimate the following regression model for the change in overnight stays for district d by quarter q in year t ,

$$\Delta\%tourism_{d,q,t} = \beta_0 + \Delta \sum_{n=1}^4 \beta_1 xeno_{d,q-n,t} + \delta_t + \phi_q + v_d + \phi_q \times \delta_t + \Delta X'_{d,q,t-1} \psi + \varepsilon_{d,q,t} \quad (1)$$

where the outcome variable *tourism* is the quarterly percentage change in overnight stays. Later regressions use as the dependent variable overnight stays for foreign and domestic tourists, the number of guests and the average duration of the visits. $xeno_{d,q,t}$ is our main variable of interest and is defined as the number of either xenophobic demonstrations, assault, arson attacks or miscellaneous attacks. We look at four quarter lags to take the delayed response in tourism demand into account.

Features such as natural characteristics, tourism attractions, the connectiveness and other unobserved characteristics could be both related to tourism attractiveness and xenophobic attitudes and obscure the causal relationship. First-differencing the data nets out these time invariant variables. Long-term growth trends in tourism can differ across districts, and we introduce district fixed effects v_d to allow for specific time trends for each district. Seasonal fixed effects ϕ_q and year fixed effects δ_t control for seasonal trends in tourism and shocks over time. These include developments that affect tourism demand on the national level. It makes our estimate a lower bound of the effect if incidents lead to a an overall reduction in tourism demand for Germany. Quarter- year fixed effects $\phi_q \times \delta_t$ cover for changes in seasonal effects. The focus on the growth rate over time and the use of fixed effects takes care of many confounding factors, and to this we add time-varying control variables that potentially explain tourism demand.

The vector $X'_{d,q,t}$ comprises control variables that may affect tourism demand. Table 2 provides the summary statistics. We include the first difference of *unemployment*, *crime per capita* and *gdp per capita*,⁵ all factors that contribute to the attractiveness of a region for tourism.

We have coded indicators for federal or state horticulture shows (*Bundesgartenschau* and *Landesgartenschau*) and major sports events (*Sportevent*) in a district as potential tourist attractions.⁶ We created data on hours of sunshine *sun*, the amount of rain *rain* and the average temperature *temp* per district with inverse distance weighting on information collected at weather sta-

⁵The monthly unemployment numbers stem from the Federal Employment Agency of Germany. Annual crime per capita statistics are from the German Federal Criminal Police and GDP per capita is from the Statistical Office of the States in Germany. All data is adjusted to match quarterly frequency.

⁶*Sportevent* is defined as a European or World championship in one of the 20 most popular sports in Germany which lasts for at least two days.

tions. The German Meteorological Service provides the weather data (*Deutscher Wetterdienst*). Last, we include data from the Federal Statistical office on the per capita change in refugee numbers in each county.

Table 2: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Overnight stays	6,381	276,096.3	550,391.0	7,771.0	8,971,198.0
Overnight stays domestic	6,381	226,566.9	384,822.7	5,825.0	4,762,345.0
Overnight stays foreign	6,381	49,529.4	208,647.2	284.0	4,309,604.0
arrivals	6,375	105,737.1	224,009.5	4,457.0	3,587,063.0
arrivals domestic	6,375	83,845.0	146,206.1	3,731.0	2,134,449.0
arrivals foreign	6,375	21,892.1	84,337.9	82.0	1,519,579.0
duration	6,375	2.6	0.9	1.4	7.6
duration domestic	6,375	2.6	0.9	1.4	7.7
duration foreign	6,375	2.4	0.8	1.2	11.7
cases	6,384	1.1	3.2	0	115
miscellaneous_attack	6,384	0.8	2.3	0	88
arson	6,384	0.05	0.3	0	9
assault	6,384	0.2	0.6	0	14
demonstration	6,384	0.1	0.6	0	23
rain	6,384	62.9	25.1	11.1	190.3
sun	6,384	136.8	62.8	33.0	255.9
temperature	6,384	10.0	5.5	0.3	19.4
crimepc	6,384	0.1	0.03	0.02	0.2
gdppc	6,384	34,777.3	14,650.7	14,716.1	138,663.9
pop	6,384	204,140.7	236,604.3	34,048.0	3,584,326.0
unemp	6,384	0.1	0.03	0.01	0.2
refugeesp	6,373	0.01	0.01	0.001	0.1
Bundesgartenschau	6,384	0.001	0.04	0	1
Landesgartenschau	6,384	0.01	0.1	0	1
sportevent	6,384	0.001	0.02	0	1
heritage site	6,384	0.3	0.4	0	1
health resort	6,384	0.6	1.1	0	5
Ski	6,384	0.1	0.3	0	1
Lake	6,384	0.1	0.3	0	1
coast	6,384	0.1	0.3	0	1
big city	6,384	0.2	0.4	0	1
amusement park	6,384	0.2	0.4	0	1
border	6,384	0.2	0.4	0	1
Distance_highway	6,384	7,760.1	8,171.7	79.8	43,022.4
Distance_train	6,384	16,808.1	15,239.2	75.4	81,720.6
Distance_airport	6,384	45,730.6	25,109.6	2,395.1	137,850.6

We then extend the analysis to estimate heterogeneous reactions of tourist depending on their origin. The percentage change in overnight stays of domestic and foreign tourists serve as a dependent variable. In another extension we distinguish the effect on overnight stays into the two components arrivals and the average duration of the stay.

As mentioned before, the per capita number of incidents might be the correct measurement of xenophobic incidents and we substitute it in as the dependent variable.

4.1.2 Results

The results from our regressions based on how the different categories of xenophobic activities might impact overnight stays are reported in Table 3. Each of the four columns reports a different category. We find that xenophobic demonstrations are associated with a statistically significant decrease in the number of overnight stays. One additional demonstration in a quarter reduces the growth of overnight stays by about one percentage point in the first and by another percentage point in the second quarter after the incident. The impact takes two quarters to play out, which is in line with the expected delay in the reaction of tourists.

On the temporal dimension of the effect, we find a weakly significant effect for a partial reversion after four quarters. We see a negative reaction in tourism numbers to assaults with a two period delay. There is no significant effect in tourism as a reaction to the two other categories. The analysis is based on data for all publicly known incidents of xenophobic activities. This also includes minor attacks and other minor events. Under the assumption that assaults and demonstrations gain more attention in the media than the other categories, our result are plausible and hints at media outlets as a key transmission channel. We will further discuss this channel in section 4.2.

We observe that counties plagued by higher unemployment rates experience an increase in tourism numbers. Fewer resources and economic uncertainty can deter locals from travelling abroad, and local destinations can act as a substitute destination and gain visitors. National horticulture shows are successful in attracting visitors to the hosting counties and increase tourism numbers, while regional horticulture shows and sports events do not. In terms of weather effects, tourism demand is highest in periods with low temperature, many sun hours and a large amount of rain.

In Column 1 and 2 of Table 4 we measure the impact of demonstrations by tourists' place of origin. Domestic tourists adjust their travelling behavior in the first and second quarter after demonstrations, while foreign visitors react with a longer delay; we can only see a significant affect in the second quarter after the incident. The quicker reaction of domestic tourism may well be due to a larger proportion of short-term trips, while foreigners plan their trips well in advance. In Column 3 and 4 we find that the effect on overnight stays is driven by a decrease in the number of arrivals and not by a shorter duration of trips.

Table 3: Effect of xenophobic activities on overnight stays

	<i>Dependent variable:</i>			
	(Growth_ueb)			
	(1)	(2)	(3)	(4)
lag(Growth_miscellaneous_attack, 1)	-0.002 (0.001)			
lag(Growth_miscellaneous_attack, 2)	0.001 (0.002)			
lag(Growth_miscellaneous_attack, 3)	0.001 (0.002)			
lag(Growth_miscellaneous_attack, 4)	0.004 (0.003)			
lag(Growth_assault, 1)		0.002 (0.006)		
lag(Growth_assault, 2)		-0.012* (0.007)		
lag(Growth_assault, 3)		0.0003 (0.008)		
lag(Growth_assault, 4)		0.007 (0.009)		
lag(Growth_arson, 1)			-0.012 (0.009)	
lag(Growth_arson, 2)			0.001 (0.014)	
lag(Growth_arson, 3)			0.017 (0.018)	
lag(Growth_arson, 4)			-0.001 (0.011)	
lag(Growth_demonstration, 1)				-0.010* (0.005)
lag(Growth_demonstration, 2)				-0.008** (0.004)
lag(Growth_demonstration, 3)				-0.004 (0.005)
lag(Growth_demonstration, 4)				0.009* (0.005)
District Fixed Effects	Yes	Yes	Yes	Yes
Seasonal Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Seasonal-Year Fixed Effects	Yes	Yes	Yes	Yes
District-level controls	Yes	Yes	Yes	Yes
Observations	4,773	4,773	4,773	4,773
R ²	0.022	0.023	0.022	0.023
F Statistic (df = 14; 4349)	7.090***	7.254***	7.098***	7.163***

Note:

*p<0.1; **p<0.05; ***p<0.01

Standard errors are heteroskedasticity robust and clustered at district level. The unit of observation is the district and quarter and covers the period from 2014 until 2017 quarter 4.

The tourists who visit a destination do not limit the duration of their stay, but they also do not prolongue it due to potentially lower costs. Tourists refrain from visiting a district that exhibits a high number of xenophobic activities, while the average duration of the remaining trips remains the same.

Table 4: Effect of xenophobic activities on locals versus foreigners and on number of stays versus duration of stay

	<i>Dependent variable:</i>			
	(Growth_nights_domestic) (1)	(Growth_nights_foreign) (2)	(Growth_arrivals) (3)	(Growth_duration) (4)
lag(Growth_demonstration, 1)	-0.010* (0.005)	-0.014 (0.011)	-0.010* (0.006)	-0.0002 (0.005)
lag(Growth_demonstration, 2)	-0.008** (0.004)	-0.017** (0.007)	-0.009** (0.004)	0.001 (0.004)
lag(Growth_demonstration, 3)	-0.005 (0.005)	-0.010 (0.010)	-0.007 (0.005)	0.004 (0.005)
lag(Growth_demonstration, 4)	0.007 (0.005)	0.008 (0.008)	0.009 (0.005)	0.001 (0.005)
District Fixed Effects	Yes	Yes	Yes	Yes
Seasonal Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Seasonal-Year Fixed Effects	Yes	Yes	Yes	Yes
District-level controls	Yes	Yes	Yes	Yes
Observations	4,773	4,773	4,763	4,763
R ²	0.023	0.012	0.033	0.026
F Statistic	7.266*** (df = 14; 4349)	3.753*** (df = 14; 4349)	10.610*** (df = 14; 4339)	8.113*** (df = 14; 4339)

Note:

*p<0.1; **p<0.05; ***p<0.01

Standard errors are heteroskedasticity robust and clustered at district level. The unit of observation is the district and quarter and covers the period from 2014 until 2017 quarter 4.

Domestic tourists are behind the positive effect of *Bundesgartenschau* and they prefer places with more sun hours and rain. A larger proportion of refugees is associated with a larger number of foreign visitors (see A4).

The results of xenophobic incidents per capita on tourism support our findings (see table 5). Assaults and demonstrations have negative repercussions on tourism, and now tourism shows a negative reaction to arson attacks. We have run the regression with state-specific seasonal effects, and they do not change the effect of demonstrations on both total tourism numbers and the disaggregated effect on tourists by origin and arrivals.

The consistent finding is that demonstrations have a negative effect on tourism. But why is there an effect for demonstrations and often not for the other categories? Media coverage serves as one explanation and we analyze this transmission channel in the next section.

Table 5: Effect of xenophobic activities per capita on overnight stays

	<i>Dependent variable:</i>			
	(Growth_ueb)			
	(1)	(2)	(3)	(4)
lag(Growth_pmiscellaneous_attack, 1)	-222.536 (354.553)			
lag(Growth_pmiscellaneous_attack, 2)	892.331* (474.884)			
lag(Growth_pmiscellaneous_attack, 3)	-208.837 (434.770)			
lag(Growth_pmiscellaneous_attack, 4)	156.165 (539.129)			
lag(Growth_passault, 1)		-441.883 (806.710)		
lag(Growth_passault, 2)		-2,114.454** (844.052)		
lag(Growth_passault, 3)		-175.681 (1,039.360)		
lag(Growth_passault, 4)		862.552 (1,071.630)		
lag(Growth_parson, 1)			-4,323.003** (1,835.156)	
lag(Growth_parson, 2)			-3,242.581 (2,353.101)	
lag(Growth_parson, 3)			-167.942 (3,233.948)	
lag(Growth_parson, 4)			-401.717 (2,490.872)	
lag(Growth_pdemonstration, 1)				-2,778.540*** (992.970)
lag(Growth_pdemonstration, 2)				137.718 (1,232.300)
lag(Growth_pdemonstration, 3)				-178.968 (1,375.400)
lag(Growth_pdemonstration, 4)				430.133 (835.320)
District Fixed Effects	Yes	Yes	Yes	Yes
Seasonal Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Seasonal-Year Fixed Effects	Yes	Yes	Yes	Yes
District-level controls	Yes	Yes	Yes	Yes
Observations	4,773	4,773	4,773	4,773
R ²	0.023	0.023	0.022	0.022
F Statistic (df = 14; 4349)	7.459***	7.245***	7.062***	7.059***

Note:

*p<0.1; **p<0.05; ***p<0.01

Standard errors are heteroskedasticity robust and clustered at district level. The unit of observation is the district and quarter and covers the period from 2014 until 2017 quarter 4.

4.2 Extension: Media

Variation in media attention towards xenophobic incidents is one explanation for the heterogeneous effects of incidents on tourism. We first introduce the media data and analyze if the media reacts differently to incidents depending on their categorization. Then, we test if media reports on xenophobic incidents lead to tourists reactions away from the affected destination.

To measure media attention, we turn to the main daily newspapers in Germany.⁷ The newspapers include *Handelsblatt*, *Welt*, *Frankfurter Allgemeine Zeitung* and *Tageszeitung*. They constitute a major part of the national newspaper market.⁸

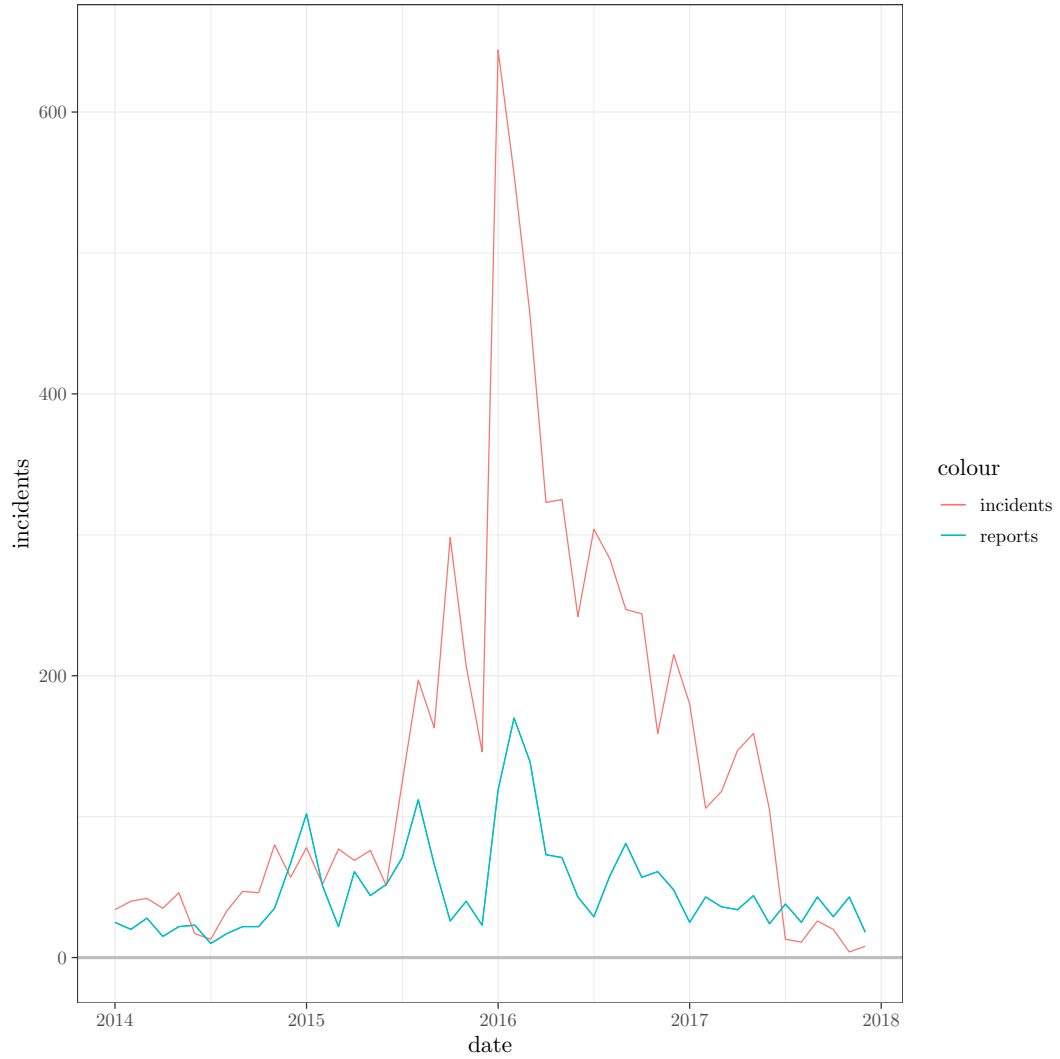
We assessed the newspapers through the newspaper repository *Genios* and the digital archives of the newspapers. In the repositories we retrieved with a search syntax all articles between the years 2012 and 2018 that dealt with xenophobic incidents (see Appendix syntax for specifics of the search syntax). We then created an algorithm that searches for city names⁹ within the articles and assigns a score of one if a city name appeared in the article. The scores are aggregated at the county level, and we get an indicator of the number of articles per county per week. Overall we collected 3154 articles that include 3991 location mentions. Berlin with 517 mentions is the most covered county, followed by Dresden with 260 mentions. Cities in 258 counties were mentioned, while the rest did not appear. The number of articles fluctuates a lot over time (see weekly data in Figure A3). Anecdotal evidence corroborates the appropriateness of our media data. The peaks coincides with the beginning of the well-known anti-refugee demonstrations in Dresden at the end of 2014, the attacks in Clausnitz at the beginning of 2016 and the xenophobic riots in Chemnitz in September 2018.

⁷Tourists can inform themselves through other media channels such as television coverage or social media. Scholars are increasingly using twitter data and Facebook postings to measure the effect of media on social outcomes (Muller and Schwarz (2018), Mitts (2019), Bursztyn et al. (2019)). We do not say that all potential visitors read the newspapers in our sample, but they serve as a proxy for the ascribed newsworthiness of events.

⁸We plan to add reports from the *Süddeutsche Zeitung* in the near future.

⁹The list includes the names of the 2000 largest German cities

Figure 5: Media Attention



Development by month

Our first interest is in the relationship between xenophobic incidents and their media attention. We find that the total number of incidents is highly correlated with the number of reports in a month. The more incidents happen in a month, the more newspaper articles cover the topic on xenophobic incidents. The graphical representation of the monthly variations in Figure 5 shows the similarity between the two datasets, both having a common peak in the

beginning of 2016. While the search syntax does not allow us to separate the reports into different categories of covered crimes, we can estimate the effect of the different xenophobic incidents on media attention $reports_{d,q,t}$ of county d in quarter q of year t by

$$reports_{d,t} = \beta_0 \Delta \beta_1 xeno_{d,q-n,t} + \delta_t + \varepsilon_{d,t} \quad (2)$$

$xeno_{d,q,t}$ again measures the number of either xenophobic demonstrations, assault, arson attacks or miscellaneous attacks. We expect that news reports follow the number of incidents. There is the possibility that news coverage of xenophobic incidents varies by the salience of the topic or that it is crowded out by other newsworthy events. This should affect reporting on all counties and we mitigate the problem by including time fixed effects. News coverage is usually short lived and our preferred specification uses weekly data. Regression (1) in table 6 reports the results of the regression.

An increase in the number of the four incident types leads to a significantly higher media attention towards xenophobic incidents for the respective county. The effect of demonstrations shows the largest magnitude, where one demonstration produces on average .25 articles within the week. Assaults have the second strongest effect, and arson attacks and miscellaneous attacks follow. The result is robust to the exclusion of Berlin and holds for monthly and quarterly data (table 7). The association between incidents and the reporting fulfills a necessary requirement for the media attention channel.

The second requirement is an effect of media reports on the destination choice of tourists. We use the first-differenced equation 1 but replace the number of xenophobic incidents with the number of news article per county per quarter for the period from 2014 to 2017. The media data covers German newspapers that target a domestic audience and should affect the decision of domestic tourists. Our outcome of interest is the number of overnight stays for domestic tourists. The results are presented in table 7. Reports on xenophobic incidents lead to less overnight stays for the first two quarters. One additional article decreases reduces the growth of overnight stays of domestic tourists by about 0.5 percent-

Table 6: Effect of xenophobic activities on media attention

	<i>Dependent variable:</i>	
	reports	
	(1)	(2)
arson	0.140** (0.058)	0.481** (0.244)
miscellaneous_attack	0.139** (0.066)	0.315*** (0.081)
demonstration	0.249*** (0.075)	0.629*** (0.123)
assault	0.174*** (0.060)	0.578* (0.333)
Time Fixed Effects	Yes	Yes
Data	weekly	monthly
Observations	83,408	6,400
R ²	0.046	0.350
F Statistic	1,009.713*** (df = 4; 83196)	310.952*** (df = 4; 6396)

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors are heteroskedasticity robust and clustered at district level. The unit of observation is the district and (1) week and (2) quarter and covers the period from 2014 until 2017.

age point in the first and by another 0.5 a percentage point in the second quarter after the incident. However, we observe that in the third and fourth quarter overnight stays significantly increase. The magnitude is about the same as the loss in the first two quarters, tourism numbers catch up to their old growth path. The coefficients of the control variables mostly remain the same. Now, percentage change in gdp per capita has a negative association with tourism numbers in overnight stays. The argument is, as for the effect of unemployment, that under higher gdp per capita growth tourists might substitute domestic travels with foreign trips.

In Table A5 we measure the impact of reports with xenophobic incidents on the other outcome measures of domestic tourism. The percentage change in arrival numbers confirms the reaction of tourists to media attention, with a significant decrease in the first two quarters and a significant pick up in the third and fourth quarter. For the duration of visits, we observe a small increase in days spent at a destination in the second quarter. In line with hypothesis (1c) the explanation is that in response to a lower demand, hotels can be intrigued to lower their prices. Tourists who travel to a destination can then afford to stay longer. The indicator of media reports is limited to German newspapers. Media coverage is highly correlated across countries, and we can use the indicator as a proxy for international media coverage. Media reports are associated with a decrease in overnight stays of international tourists in the first two quarters. The magnitude of the effect is twice as large as for domestic tourists. Though we observe a partial reversion in the fourth quarter, the aggregated effect over the four quarters is negative.

4.3 Extension: Synthetic Control Method

Overview

In order to illustrate how xenophobic incidents can affect tourism, we conduct a case study on the county Dresden. Dresden is one of the main tourist destinations in Germany. In 2013, almost two million tourists spent one night or more in the city. But Dresden also became home to one of the largest anti-refugee organisations in Germany, the so-called *Pegida*.¹⁰ The movement organised weekly demonstrations against refugees and received large coverage in national and international media. Overall, Dresden experienced the second largest num-

¹⁰Patriotic Europeans Against the Islamisation of the Occident

Table 7: Effect of xenophobic activities on media attention

	<i>Dependent variable:</i>
	(Growth_ueb'in)
lag(Growth_unemp, 1)	7.553*** (2.831)
lag(Growth_crimepc, 1)	0.137 (0.143)
lag(Growth_gdppc, 1)	-0.685** (0.317)
Growth_sport	0.143 (0.137)
Growth_landesgs	-0.154 (0.106)
Growth_bundesgs	0.746*** (0.286)
lag(growth_temperature, 1)	-0.018** (0.008)
lag(growth_sun, 1)	0.001*** (0.0004)
lag(growth_rain, 1)	0.001*** (0.0002)
lag(Growth_refugeesp, 1)	0.061 (0.047)
lag(Growth_reports, 1)	-0.004* (0.002)
lag(Growth_reports, 2)	-0.005*** (0.002)
lag(Growth_reports, 3)	0.005** (0.002)
lag(Growth_reports, 4)	0.005* (0.003)
District Fixed Effects	Yes
Seasonal Fixed Effects	Yes
Year Fixed Effects	Yes
Seasonal-Year Fixed Effects	Yes
District-level controls	Yes
Observations	4,377
R ²	0.027
F Statistic	7.796*** (df = 14; 3954)

Note:

*p<0.1; **p<0.05; ***p<0.01

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Standard errors are heteroskedasticity robust and clustered at district level. The unit of observation is the district and (1) week and (2) quarter and covers the period from 2014 until 2017.

ber of anti-refugee incidents across German counties and gained notoriety as a place of anti-refugee sentiment.

The preferred empirical strategy would be a comparison of tourism in Dresden around the incidents to a counterfactual Dresden in the absence of such a shock. As no counterfactual exists, a comparative case study approach offers an alternative. Counties that mimic the tourism industry of Dresden but were unaffected by the shock constitute an appropriate comparison group.

The Synthetic Control Method (SCM) provides for a data-driven approach to select a comparison group. It was developed by Abadie and Gardeazabal (2003) and extended in Abadie et al. (2010). The SCM creates a counterfactual, or a synthetic control, of the treated unit by weighing a small number of control units. For our case, these control units should closely match tourism in Dresden in the years prior to the xenophobic incidents. A comparison of the outcome of Dresden and its synthetic control after the intervention informs us about the treatment effect. Formally this works as follows.

The model

There are $J + 1$ units or counties indexed by subscript i . $i = 1$ represents the unit exposed to the treatment, which in our case is Dresden. Units $i = 2$ to $i = J + 1$ are the counties that constitute the donor pool. The treatment of xenophobic incidents starts in period T_0 and there are T_0 pre-intervention periods with $1 \leq T_0 < T$.

Y_{1t}^I is the observed outcome of Dresden that is exposed to the treatment at time t , Y_{1t}^N is the outcome of a counterfactual Dresden with no treatment.

In the period $t \in 1, \dots, T_0$ before the treatment, the intervention should have no effect on the outcome, so $Y_{1t}^I = Y_{1t}^N$.

Our outcome of interest is the treatment effect which we define as $\alpha_{1t} = Y_{1t}^I - Y_{1t}^N$ at time t . For $t > T_0$, the treatment effect measures how much tourism changes due to the xenophobic shock.

Let D_{1t} be an indicator with the value of one if the unit is exposed to the treatment at time t and zero otherwise. Then we can say that the outcome of unit 1 at time t is $Y_{1t} = Y_{1t}^N + \alpha_{1t}D_{1t}$.

The outcome Y_{1t}^I of a Dresden with the xenophobic treatment is observable, but the hypothetical outcome Y_{it}^N with no treatment is unknown.

For measuring the treatment effect, we need to estimate Y_{1t}^N . Following Abadie et al. (2010), we model the outcomes as

$$Y_{1t}^I = \rho_t + \alpha_{1t}D_{1t} + v_{1t}$$

$$Y_{1t}^N = \rho_t + v_{1t}$$

Setting up the model

Besides the treatment effect, the potential outcomes depend on a common time varying factor ρ_t and the error term v_{it} .

Suppose that v_{1t} is represented by the model $v_{1t} = \theta_t Z_1 + \lambda_t \omega_1 + \epsilon_{1t}$.

where Z_1 is a vector of independent variables unaffected by the treatment, θ_t is a vector of time specific parameters, λ_t an unknown common factor, ω_1 represents country-specific unobservables and ϵ_{1t} is an error term with transitory shocks of mean zero.

An estimation of a weighted average of Y_{it} for $i = 2, \dots, J + 1$ for the period $t < t_0$ gives us the counterfactual Y_{it}^N while taking into account the covariates Z .

For this we use a $J \times 1$ vector of weights $W = (w_2, \dots, w_{J+1})'$ such that $w_j \geq 0$ for $j = 2, \dots, J + 1$ and $\sum w_j = 1$

Each choice of W is a potential synthetic control for Dresden and provides a weighted average of the units in the donor pool. W should be selected so that the synthetic control best resembles the characteristics of tourism in Dresden in the pre-treatment period.

As long as we can choose w such that

$$\sum_{i=2}^{J+1} w_i^* Y_{it} = Y_{1t} \text{ and } \sum_{i=2}^{J+1} w_j^* Z_j = Z_1,$$

we get the choice of the optimal set of weights W^* . Often an exact weighting does not exist, but as long as the weighted combination approximates the outcome well the results are deemed trustworthy.

Selecting w

Let the $(k \times 1)$ vector X_1 contain the values of the values of k characteristics of the treated unit in the pretreatment period. The $(k \times k)$ matrix X_0 contains the values of the characteristics of the donor countries in the pretreatment period. X_1 and X_0 can include the pre-intervention outcome values. Vector $X_1 - X_0 W$ gives the difference between the pre-intervention characteristics of the treated unit and the synthetic control. The optimal weight W^* is chosen as to minimise this difference.

The estimation is operationalized in the following. For $m = 1, \dots, k$ let X_{1m} be the value of the m -th variable of the treated unit and let X_{0m} be a $(1 \times J)$ vector of the values for the m -th value of the units in the donor pool. Then we choose W^* as the value that minimizes

$$\sum_{m=1}^k v_m (X_{1m} - X_{0m}W)^2$$

where v_m reflects the relative importance that is assigned to the m -th variable. Variables that have a large predictive power on the outcome of the unit with an intervention gain a large v_m weight.

Using the optimal weight W^* , the treatment effect can be estimated by

$$\hat{\alpha}_i t = Y_{1t} - \sum_{i=2}^{J+1} w_i^* Y_{it} \text{ for all } t \geq T_0$$

The Case of Dresden

The donor pool should be restricted to counties that exhibit similar characteristics to the treated unit. Otherwise, differences in the outcomes might reflect disparities in regional characteristics and not the treatment effect. Dresden is one of the largest cities in Germany and we include German counties with a city over 500.000 inhabitants into our donor pool. These are Berlin, Hamburg, Munich, Frankfurt, Cologne, Düsseldorf, Stuttgart, Nürnberg, Hannover and Bremen. We exclude Leipzig and Berlin as they exhibited considerable anti-refugee movements themselves and the closeness of Leipzig to Dresden raises the concern of spillovers. Another requirement is that the donor counties do not experience idiosyncratic shocks in the outcome during the sample period.

The pre-treatment predictors should include variables that well-approximate the path of tourism in Dresden. We test for the correlations between potential tourism determinants and the outcome variable *overnight_stays*. Table A6 shows the results of an OLS regression in a pooled sample in the period of interest. Most of the variables are valid predictors of tourism numbers. The rate of unemployment is lower in touristic areas as is the crime rate. Large sports events, being home to a cultural heritage and amusement parks attract tourism, and counties that have a coastal area are popular destinations. Further, the distance to the highway is positively correlated with the number of overnight stays and a large distance to an airport discourages foreign guests. The weather plays a role as areas with lower temperature and more hours of sunshine are successful in attracting tourists.

Our sample is aggregated into quarterly intervals. Tourism numbers are prone to seasonal variation. We want to differentiate between movements due to xenophobia and seasonal swings and de-seasonalize the data by a rolling mean of 4 periods. Counties become more similar to each other which facilitates the creation of a synthetic control, though we lose the first 3 quarter periods in the pre-treatment period. We assume that seasonal variation did not change after the treatment.

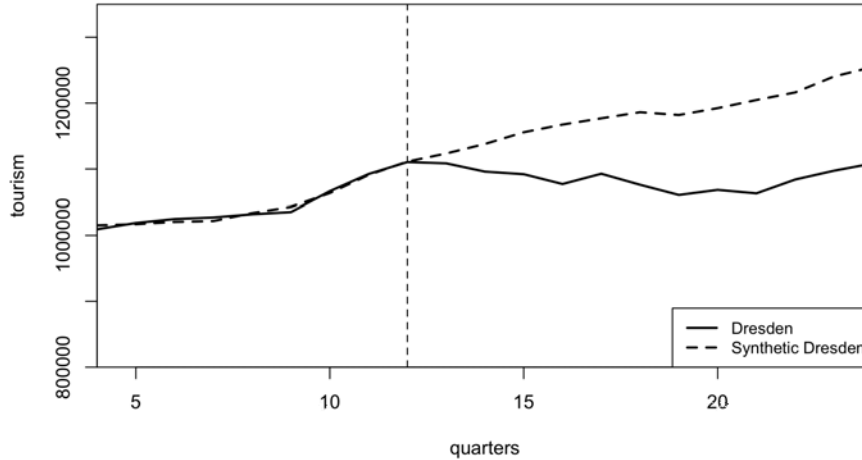
Demonstrations of the Pegida movement started in the second half of 2014. Figure A4 shows the weekly number of protesters. The numbers peaked in the beginning of 2015 but remained on a noticeable level until the end of our sample. We choose the fourth quarter of 2014 as the point of treatment after which Dresden's image turned xenophobic.

The results on the determinants of tourism in table A6 serve as the basis for selecting characteristics X . We use their mean value as predictors in the weighting estimation. To this, we add every second outcome value of *overnight_stays* in the pre-intervention period, starting in the fourth quarter of 2012 .

The SCM explicitly tells us the relative contribution of each control unit. The weighting that best approximates Dresden consists to 56.3 percent of Dortmund, to 21.1 per cent of Stuttgart, to 13 per cent of Bremen and to low percentages of the other counties (see table A8). In Table A7 we can observe that the weighting was successful in making the characteristics of the synthetic control more similar to Dresden compared to the mean values of the donor pool in the pre-intervention period.

Figure 6 depicts the development of overnight stays over time for Dresden and its synthetic counterpart. In the pre-intervention period, tourism in the synthetic Dresden follows the observed outcome of Dresden closely. Shortly after the treatment in 2014 Q4, tourism numbers of Dresden drop, while the numbers of synthetic Dresden continue to grow. There is a negative treatment effect of xenophobic incidents over the whole post-intervention period. At the end of the sample, the treatment effects accounts for about 138,000 overnight stays per quarter, or a loss of 11.1 percent of potential overnight stays in the fourth quarter of 2017. The evidence suggests that the xenophobic incidents led to a large decrease in tourism for Dresden.

Figure 6: Synthetic control of Dresden



Dresden and the synthetic control of Dresden.

The synthetic control method rests on two assumptions. First, the variables in X_1 in the pre-treatment period should not anticipate effects of the treatment. The demonstrations in Dresden and the xenophobic incidents were regarded as a reaction to the refugee crisis. The refugee crisis came unexpected and we do not expect anticipation effects from xenophobic incidents. Xenophobic activities should only have an effect on tourism after the incident.

Second, the treatment should not affect the counties in the donor pool. Xenophobic activities happened across Germany and all large cities experienced incidents. But we argue that some counties such as Dresden were much more affected by xenophobia than the others. As we have excluded Leipzig and Berlin, the sample comprises counties that were characterized by a low intensity of xenophobia. If counties with positive weight in the weight matrix experienced xenophobic incidents and a subsequent decrease in tourism, this would bias the synthetic control for Dresden downwards and the estimation would generate a lower bound of the true treatment effect. The same bias would appear if the incidents in Dresden led to a worse image of Germany and to a decrease in tourism across all German counties.

To test the robustness of the results, we conduct placebo tests on the units that were not exposed to the xenophobic shock. We reassign the treatment to the untreated units that are part of the donor pool and for each we estimate a synthetic control. The estimated effect of the xenophobic shock on Dresden can be then evaluated in light of the distribution of the placebo effects for the other units. If our estimation is robust, we expect that the treatment effect of Dresden is relatively large compared to the other placebo effects. In the estimation we exclude counties where the fit of the pre-treatment period is poor. The Root Mean Squared Prediction Error (RMSPE) measures the magnitude in the gap between outcome and the synthetic control in the pre-intervention period and allows a statement about the fit. It includes counties that have an RMSPE only 10 times the RMSPE from Dresden. Figure A5 shows that the treatment effect for Dresden is larger than for all the synthetic controls of the placebo tests. It increases our confidence that it is not random shocks that drive the results but that we observe the true treatment effect of xenophobic incidents.

In a second step we report the ratio between the post and pre-intervention RMSPE for Dresden and the units in the donor pool. As long as the synthetic control mimics the outcome in the pre-intervention well, a large ratio tells us that there is a large treatment effect for the unit. Again Dresden is far ahead compared to the other counties in the sample and has a ratio that is three times larger than for the second county (see Figure A6).

5 Conclusion

To sum up, we have shown that xenophobic incidents have a negative impact on tourist arrivals. Tourism numbers decrease in the first two quarters after an incident, but recover again after one year. The media attention towards the incidents is the driving factor that leads to the reaction of tourists to not visit a destination. This finding shows an economic cost of xenophobic activities that has not received attention before. It provides a first step to gain a better understanding of the direct economic costs of xenophobic activities.

The economic costs of hate crimes for German counties are non-negligible. Some of the most affected vicinities such as Dresden or the Sächsische Schweiz are popular tourist attractions and the decline in tourism numbers has grave effects for the local economy. Our estimate is a lower bound of the true economic costs of xenophobic activities. Tourism is only part of the story as the diminished attractiveness of a district can have repercussions on potential investors and workers.

While our focus on a single country comes with advantages in the empirical setup, future research could address the topic for a broader set of countries and longer time periods.

The economic costs of xenophobia discussed above provide support for political action, for example in the areas of integration and prevention of xenophobia. The key advantage of our finding is that it is fact-based and empirically tested instead of relying on moral or political ideologies.

Bibliography

References

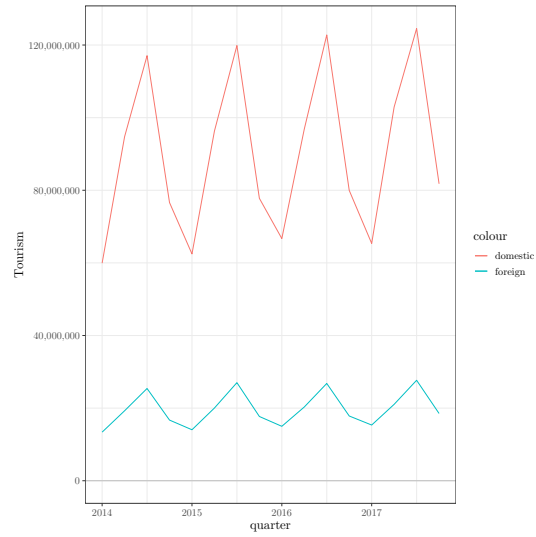
- Abadie, A., A. Diamond, and J. Hainmueller (2010). Synthetic control methods for comparative case studies: Estimating the effect of california’s tobacco control program. *Journal of the American Statistical Association* 105(490), 493–505.
- Abadie, A. and J. Gardeazabal (2003, March). The economic costs of conflict: A case study of the basque country. *American Economic Review* 93(1), 113–132.
- Ahlfeldt, G. M., B. Franke, and W. Maennig (2015). Terrorism and international tourism: the case of germany. *Jahrbücher für Nationalökonomie und Statistik* 235(1), 3–21.
- Benček, D. and J. Strasheim (2016). Refugees welcome? A dataset on anti-refugee violence in Germany. *Research & Politics* 3(4), 1–11.
- Bursztyn, L., G. Egorov, R. Enikolopov, and M. Petrova (2019). Social media and xenophobia: Evidence from russia. NBER Working Papers 26567, National Bureau of Economic Research, Inc.
- Dahl, G. and S. DellaVigna (2009). Does movie violence increase violent crime? *The Quarterly Journal of Economics* 124(2), 677–734.
- DellaVigna, S. and E. Kaplan (2007). The fox news effect: Media bias and voting. *The Quarterly Journal of Economics* 122(3), 1187–1234.
- Eisensee, T. and D. Strömberg (2007). News droughts, news floods, and u. s. disaster relief. *The Quarterly Journal of Economics* 122(2), 693–728.
- Entorf, H. and M. Lange (2019). Refugees welcome? understanding the regional heterogeneity of anti-foreigner hate crimes in germany. *ZEW Discussion Papers* (19-005).
- Faber, B. and C. Gaubert (2019, June). Tourism and economic development: Evidence from mexico’s coastline. *American Economic Review* 109(6), 2245–93.
- Falk, A., A. Kuhn, and J. Zweimüller (2011). Unemployment and right-wing extremist crime*. *The Scandinavian Journal of Economics* 113(2), 260–285.

- Friebel, G., J. M. Gallego, and M. Mendola (2013). Xenophobic attacks, migration intentions, and networks: evidence from the south of africa. *Journal of Population Economics* 26(2), 555–591.
- Gale, L. R., W. Carrington Heath, and R. W. Ressler (2002). An Economic Analysis of Hate Crime. *Eastern Economic Journal* 28(2), 203–216.
- German Travel Association (2015). The importance of tourism in Germany.
- Gould, E. D. and E. F. Klor (2016). The long-run effect of 9/11: Terrorism, backlash, and the assimilation of muslim immigrants in the west. *The Economic Journal* 126(597), 2064–2114.
- Hole, A. R. and A. Ratcliffe (2020). The impact of the london bombings on the well-being of adolescent muslims. *The Scandinavian Journal of Economics*.
- Lewis, G. and G. Zervas (2019). The supply and demand effects of review platforms.
- Mitts, T. (2019). From isolation to radicalization: Anti-muslim hostility and support for isis in the west. *American Political Science Review* 113(1), 173–194.
- Mulholland, S. E. (2013). White supremacist groups and hate crime. *Public Choice* 157(1-2), 91–113.
- Muller, K. and C. Schwarz (2018). Fanning the Flames of Hate: Social Media and Hate Crime. *SSRN Electronic Journal*.
- Neumayer, E. (2004). The Impact of Political Violence on Tourism: Dynamic Cross-national Estimation. *Journal of Conflict Resolution* 48(2), 259–281.
- Ryan, M. E. and P. T. Leeson (2011). Hate groups and hate crime. *International Review of Law and Economics* 31(4), 256–262.
- Saha, S. and G. Yap (2014). The Moderation Effects of Political Instability and Terrorism on Tourism Development: A Cross-Country Panel Analysis. *Journal of Travel Research* 53(4), 509–521.
- Sharma, S. (2015). Caste-based crimes and economic status: Evidence from India. *Journal of Comparative Economics* 43(1), 204–226.

- Steinhardt, M. F. (2018). The impact of xenophobic violence on the integration of immigrants.
- Tabellini, M. (2019). Gifts of the Immigrants, Woes of the Natives: Lessons from the Age of Mass Migration. *The Review of Economic Studies* 87(1), 454–486.
- Ziller, C. and S. W. Goodman (2020). Local government efficiency and anti-immigrant violence. *The Journal of Politics Forthcoming*.

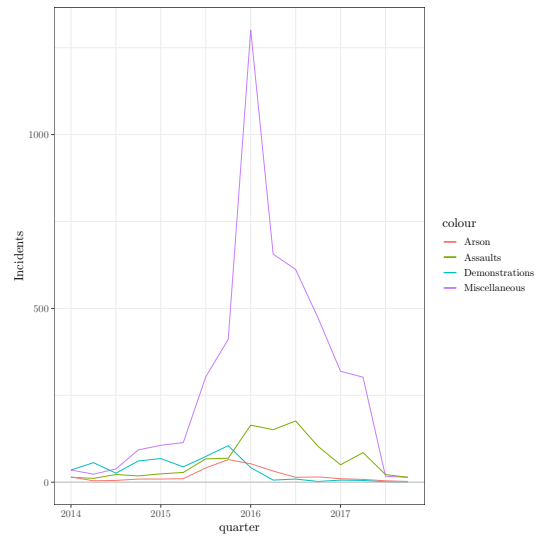
Appendix

Figure A1: Tourism development



Development of overnight stays for domestic and foreign tourists per quarter.

Figure A2: Xenophobic Incidents



Number of xenophobic incidents per quarter.

Table A1: Data Sources

Variables	Definition	Coding	Source
Overnight stays tourists	days		Statistical Offices of the German States
Overnight stays domestic tourists		days	Statistical Offices of the German States
Overnight stays foreign tourists	days		Statistical Offices of the German States
arrivals tourists	tourists		Statistical Offices of the German States
arrivals domestic tourists	tourists		Statistical Offices of the German States
arrivals foreign tourists	tourists		Statistical Offices of the German States
duration tourists	days		Statistical Offices of the German States
duration domestic tourists	days		Statistical Offices of the German States
duration foreign tourists	days		Statistical Offices of the German States
cases	incidents		Amadeu Antonio Stiftung
miscellaneous attack	incidents		Amadeu Antonio Stiftung
arson attack	incidents		Amadeu Antonio Stiftung
assault	incidents		Amadeu Antonio Stiftung
demonstration	incidents		Amadeu Antonio Stiftung
rain	litre per sqm	interpolation based on inverse distance weighting	German Meterological Service
sun	hours	interpolation based on inverse distance weighting	German Meterological Service
temperature	degree celcius	interpolation based on inverse distance weighting	German Meterological Service
crime pc	incidents per capita		German Federal Police
gdp pc	gdp per capita		Statistical Offices of the German States
population	number inhabitants		Statistical Offices of the German States
unemployment rate	percentages		Federal Employment Agency of Germany
refugees pc	persons per capita		Federal Statistical Office
Bundesgartenschau	dummy		own coding
Landesgartenschau	dummy		own coding
sportevent	dummy	European\World Championship of at least 2 days in one of the top 20 sports disciplines (viewers preferences in Germany)	own coding
heritage site	dummy		own coding
health resort	number of sites	official spas	German Heilbäderverband
Ski	dummy	skiing resorts	https://www.skiinfo.de
Lake	dummy	lake above 10km2	own coding
coast	dummy		own coding
big city	dummy	above 100,000 inhabitants	own coding
amusement park	dummy		https://www.parkerlebnis.de
border	dummy		own coding
Distance highway	kilometer		own coding
Distance train	kilometer		own coding
Distance airport	kilometer		own coding

Table A2: Effect of xenophobic activities on overnight stays

	<i>Dependent variable:</i>			
	(Growth.nights)			
	(1)	(2)	(3)	(4)
lag(Growth_unemp, 1)	6.365** (2.549)	6.416** (2.547)	6.343** (2.557)	6.404** (2.555)
lag(Growth_crimepc, 1)	0.084 (0.111)	0.082 (0.111)	0.092 (0.111)	0.077 (0.110)
lag(Growth_gdppc, 1)	0.352 (0.487)	0.362 (0.488)	0.357 (0.486)	0.343 (0.488)
Growth_sport	0.211 (0.158)	0.214 (0.155)	0.209 (0.158)	0.218 (0.164)
Growth_landesgs	-0.155 (0.099)	-0.156 (0.099)	-0.157 (0.099)	-0.157 (0.098)
Growth_bundesgs	0.718*** (0.259)	0.688** (0.282)	0.699*** (0.269)	0.688** (0.291)
lag(growth_temperature, 1)	-0.018** (0.008)	-0.018** (0.008)	-0.018** (0.008)	-0.018** (0.008)
lag(growth_sun, 1)	0.001*** (0.0004)	0.001*** (0.0004)	0.001*** (0.0004)	0.001*** (0.0004)
lag(growth_rain, 1)	0.001*** (0.0002)	0.001*** (0.0002)	0.001*** (0.0002)	0.001*** (0.0002)
lag(Growth_refugeespc, 1)	0.049 (0.045)	0.048 (0.045)	0.051 (0.046)	0.056 (0.047)
lag(Growth_miscellaneous_attack, 1)	-0.002 (0.001)			
lag(Growth_miscellaneous_attack, 2)	0.001 (0.002)			
lag(Growth_miscellaneous_attack, 3)	0.001 (0.002)			
lag(Growth_miscellaneous_attack, 4)	0.004 (0.003)			
lag(Growth_assault, 1)		0.002 (0.006)		
lag(Growth_assault, 2)		-0.012* (0.007)		
lag(Growth_assault, 3)		0.0003 (0.008)		
lag(Growth_assault, 4)		0.007 (0.009)		
lag(Growth_arson, 1)			-0.012 (0.009)	
lag(Growth_arson, 2)			0.001 (0.014)	
lag(Growth_arson, 3)			0.017 (0.018)	
lag(Growth_arson, 4)			-0.001 (0.011)	
lag(Growth_demonstration, 1)				-0.010* (0.005)
lag(Growth_demonstration, 2)				-0.008** (0.004)
lag(Growth_demonstration, 3)				-0.004 (0.005)
lag(Growth_demonstration, 4)				0.009* (0.005)
District Fixed Effects	Yes	Yes	Yes	Yes
Seasonal Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Seasonal-Year Fixed Effects	Yes	Yes	Yes	Yes
District-level controls	Yes	Yes	Yes	Yes
Observations	4,773	4,773	4,773	4,773
R ²	0.022	0.023	0.022	0.023
F Statistic (df = 14; 4349)	7.090***	7.254***	7.098***	7.163***

Note:

*p<0.1; **p<0.05; ***p<0.01

Standard errors are heteroskedasticity robust and clustered at district level. The unit of observation is the district and quarter and covers the period from 2014 quarter 4 until 2017 quarter 4.

Table A3: Effect of xenophobic activities per capita on overnight stays

	<i>Dependent variable:</i>			
	(Growth_nights)			
	(1)	(2)	(3)	(4)
lag(Growth_unemp, 1)	6.486** (2.561)	6.375** (2.552)	6.378** (2.558)	6.329** (2.473)
lag(Growth_crimepc, 1)	0.078 (0.110)	0.079 (0.111)	0.088 (0.112)	0.073 (1.108)
lag(Growth_gdppc, 1)	0.348 (0.487)	0.382 (0.488)	0.368 (0.489)	0.355 (0.488)
Growth_sport	0.211 (0.157)	0.210 (0.156)	0.209 (0.157)	0.205 (0.158)
Growth_landesgs	-0.156 (0.098)	-0.156 (0.099)	-0.159 (0.098)	-0.156 (0.099)
Growth_bundesgs	0.686** (0.288)	0.683** (0.288)	0.671** (0.290)	0.692** (0.293)
lag(growth_temperature, 1)	-0.018** (0.008)	-0.017** (0.008)	-0.018** (0.008)	-0.018** (0.008)
lag(growth_sun, 1)	0.001*** (0.0004)	0.001*** (0.0004)	0.001*** (0.0004)	0.001*** (0.0004)
lag(growth_rain, 1)	0.001*** (0.0002)	0.001*** (0.0002)	0.001*** (0.0002)	0.001*** (0.0002)
lag(Growth_refugeesp, 1)	0.047 (0.045)	0.048 (0.045)	0.054 (0.046)	0.054 (0.047)
lag(Growth_pmiscellaneous_attack, 1)	-222.536 (354.553)			
lag(Growth_pmiscellaneous_attack, 2)	892.331* (474.884)			
lag(Growth_pmiscellaneous_attack, 3)	-208.837 (434.770)			
lag(Growth_pmiscellaneous_attack, 4)	156.165 (539.129)			
lag(Growth_passault, 1)		-441.883 (806.710)		
lag(Growth_passault, 2)		-2,114.454** (844.052)		
lag(Growth_passault, 3)		-175.681 (1,039.360)		
lag(Growth_passault, 4)		862.552 (1,071.630)		
lag(Growth_parson, 1)			-4,323.003** (1,835.156)	
lag(Growth_parson, 2)			-3,242.581 (2,353.101)	
lag(Growth_parson, 3)			-167.942 (3,233.948)	
lag(Growth_parson, 4)			-401.717 (2,490.872)	
lag(Growth_pdemonstration, 1)				-2,778.540*** (992.970)
lag(Growth_pdemonstration, 2)				137.718 (1,232.300)
lag(Growth_pdemonstration, 3)				-178.968 (1,375.400)
lag(Growth_pdemonstration, 4)				430.133 (835.320)
District Fixed Effects	Yes	Yes	Yes	Yes
Seasonal Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Seasonal-Year Fixed Effects	Yes	Yes	Yes	Yes
District-level controls	Yes	Yes	Yes	Yes
Observations	4,773	4,773	4,773	4,773
R ²	0.023	0.023	0.022	0.022
F Statistic (df = 14; 4349)	7.459***	7.245***	7.062***	7.059***

Note:

*p<0.1; **p<0.05; ***p<0.01

Standard errors are heteroskedasticity robust and clustered at district level. The unit of observation is the district and quarter and covers the period from 2014 quarter 4 until 2017 quarter 4.

Table A4: Effect of xenophobic activities on locals versus foreigners and on number of stays versus duration of stay

	<i>Dependent variable:</i>			
	(Growth_ueb.in)	(Growth_ueb.aus)	(Growth_ank)	(Growth_dauer)
	(1)	(2)	(3)	(4)
lag(Growth_unemp, 1)	6.174** (2.571)	9.761* (5.643)	10.222*** (2.558)	-2.427 (2.555)
lag(Growth_crimepc, 1)	0.105 (0.113)	0.069 (0.273)	0.116 (0.100)	-0.034 (0.110)
lag(Growth_gdppc, 1)	0.292 (0.484)	0.345 (0.901)	0.230 (0.443)	0.211 (0.488)
Growth_sport	0.139 (0.127)	0.511* (0.306)	0.201 (0.210)	0.010 (0.164)
Growth_landesgs	-0.145 (0.104)	-0.145 (0.169)	-0.154* (0.082)	-0.006 (0.098)
Growth_bundesgs	0.738** (0.303)	0.108 (0.142)	0.599** (0.270)	0.074 (0.291)
lag(growth_temperature, 1)	-0.017** (0.008)	-0.030*** (0.011)	-0.007 (0.006)	-0.011 (0.008)
lag(growth_sun, 1)	0.002*** (0.0004)	0.0003 (0.001)	0.001*** (0.0003)	0.0004 (0.0004)
lag(growth_rain, 1)	0.001*** (0.0002)	0.0003 (0.0004)	0.001*** (0.0002)	0.00004 (0.0002)
lag(Growth_refugeesp, 1)	0.053 (0.049)	0.270*** (0.104)	0.096** (0.048)	-0.025 (0.047)
lag(Growth_demonstration, 1)	-0.010* (0.005)	-0.014 (0.011)	-0.010* (0.006)	-0.0002 (0.005)
lag(Growth_demonstration, 2)	-0.008** (0.004)	-0.017** (0.007)	-0.009** (0.004)	0.001 (0.004)
lag(Growth_demonstration, 3)	-0.005 (0.005)	-0.010 (0.010)	-0.007 (0.005)	0.004 (0.005)
lag(Growth_demonstration, 4)	0.007 (0.005)	0.008 (0.008)	0.009 (0.005)	0.001 (0.005)
District Fixed Effects	Yes	Yes	Yes	Yes
Seasonal Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Seasonal-Year Fixed Effects	Yes	Yes	Yes	Yes
District-level controls	Yes	Yes	Yes	Yes
Observations	4,773	4,773	4,763	4,763
R ²	0.023	0.012	0.033	0.026
F Statistic	7.266*** (df = 14; 4349)	3.753*** (df = 14; 4349)	10.610*** (df = 14; 4339)	8.113*** (df = 14; 4339)

Note:

*p<0.1; **p<0.05; ***p<0.01

Standard errors are heteroskedasticity robust and clustered at district level. The unit of observation is the district and quarter and covers the period from 2014 quarter 1 until 2017 quarter 4.

Syntax for Newspaper Articles

Reports are classified as reporting on xenophobic incidents if:

*Fremdenfeind OR Ausländerfeind OR Rassis OR Rechtsrad OR Xenoph OR
Fremdenhass OR Ausländerhass*

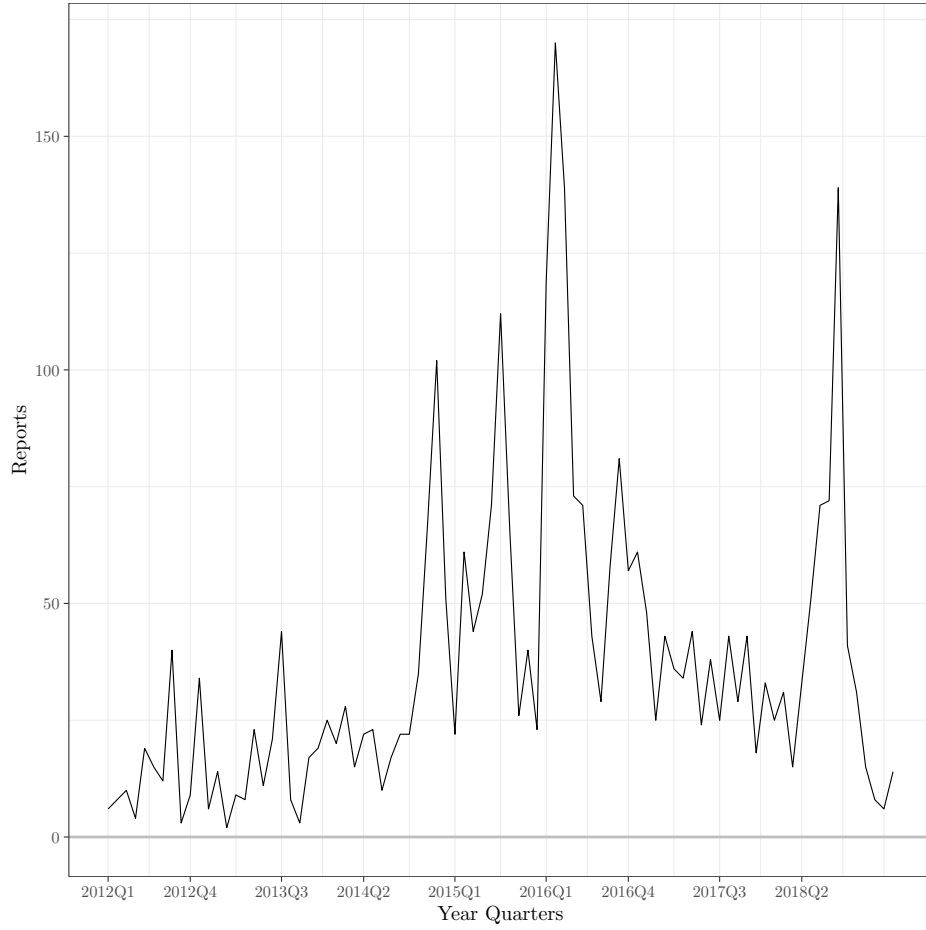
comes in the same sentence with

*Kundg OR Demo OR Protest OR Aufmarsch OR Gewalt OR Brandan OR
Brandst OR Anschlag OR Übergr OR Angr OR Körperver OR Verletz OR Droh
OR Beleid*

and in the article with

Flücht OR Flucht OR Asyl OR Geflüch

Figure A3: Media Attention



Development by week

Table A5: Effect of media reports on number of stays versus duration of stay and on the number of foreign tourists

	<i>Dependent variable:</i>		
	(Growth_ank)	(Growth_dauer)	(Growth_ueb_aus)
	(1)	(2)	(3)
lag(Growth_unemp, 1)	11.605*** (2.793)	-2.538*** (0.439)	11.907* (6.418)
lag(Growth_crimepc, 1)	0.145 (0.108)	-0.030 (0.035)	0.078 (0.275)
lag(Growth_gdppc, 1)	-0.491* (0.285)	-0.022 (0.125)	-0.755 (0.890)
Growth_sport	0.123 (0.166)	0.054* (0.031)	0.390* (0.235)
Growth_landesgs	-0.162* (0.084)	-0.007 (0.024)	-0.143 (0.175)
Growth_bundesgs	0.608** (0.250)	0.072** (0.031)	0.117 (0.121)
lag(growth_temperature, 1)	-0.007 (0.006)	-0.011*** (0.002)	-0.027** (0.011)
lag(growth_sun, 1)	0.001** (0.0003)	0.0004*** (0.0001)	-0.0002 (0.001)
lag(growth_rain, 1)	0.001*** (0.0002)	0.0001 (0.0001)	0.0004 (0.0004)
lag(Growth_refugeesp, 1)	0.101** (0.046)	-0.022** (0.010)	0.267*** (0.102)
lag(Growth_reports, 1)	-0.005** (0.002)	0.0003 (0.001)	-0.008** (0.003)
lag(Growth_reports, 2)	-0.007*** (0.002)	0.002** (0.001)	-0.012** (0.005)
lag(Growth_reports, 3)	0.005** (0.002)	0.001 (0.0004)	0.003 (0.004)
lag(Growth_reports, 4)	0.006** (0.003)	-0.0005 (0.001)	0.007** (0.004)
District Fixed Effects	Yes	Yes	Yes
Seasonal Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Seasonal-Year Fixed Effects	Yes	Yes	Yes
District-level controls	Yes	Yes	Yes
Observations	4,367	4,367	4,377
R ²	0.043	0.026	0.018
F Statistic	12.585*** (df = 14; 3944)	7.652*** (df = 14; 3944)	5.056*** (df = 14; 3954)

Note:

*p<0.1; **p<0.05; ***p<0.01

Standard errors are heteroskedasticity robust and clustered at district level. The unit of observation is the district and quarter and covers the period from 2014 quarter 1 until 2017 quarter 4.

Table A6: Determinants of the number of overnight Stays

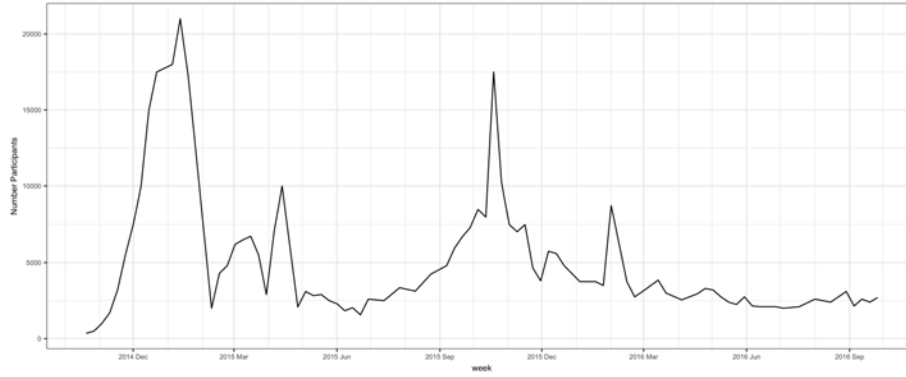
	<i>Dependent variable:</i>		
	log(Nights)	log(Nights.foreign)	log(Nights.domestic)
	(1)	(2)	(3)
unemp	-10.281*** (2.573)	-17.879*** (3.082)	-9.223*** (2.483)
crimepc	12.964*** (3.632)	19.556*** (4.310)	11.834*** (3.436)
log(gdppc)	0.180 (0.189)	0.841*** (0.218)	0.067 (0.181)
Sportevent	2.977*** (0.933)	3.779*** (1.089)	2.733*** (0.852)
Bundesgartenschau	0.691 (0.548)	0.748 (0.656)	0.655 (0.498)
Welterbe	0.207** (0.093)	0.165 (0.114)	0.223** (0.089)
Kurort	0.484*** (0.031)	0.348*** (0.043)	0.499*** (0.031)
Kueste	0.781*** (0.163)	0.317* (0.183)	0.807*** (0.168)
Freizeitpark	0.523*** (0.087)	0.519*** (0.100)	0.527*** (0.086)
distance_autobahn	0.001*** (0.001)	0.001 (0.001)	0.001*** (0.001)
distance_train	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
distance_airport	-0.000 (0.001)	-0.001*** (0.001)	-0.000 (0.001)
temperature	-0.016** (0.007)	-0.033*** (0.009)	-0.013 (0.007)
sun	0.001** (0.001)	0.003*** (0.001)	0.001 (0.001)
rain	0.002 (0.001)	0.004*** (0.001)	0.001 (0.001)
Constant	9.263*** (1.921)	0.655 (2.210)	10.230*** (1.842)
Observations	8,379	8,379	8,379
R ²	0.429	0.383	0.445
F Statistic (df = 15; 8363)	418.812***	345.416***	447.803***

Note:

*p<0.1; **p<0.05; ***p<0.01

Standard errors are heteroskedasticity robust and clustered at district level. The unit of observation is the district and quarter and covers the period from 2012 quarter 3 until 2017 quarter 4.

Figure A4: Pegida attendants



The graph shows the weekly number of pegida attendants over time.

Table A7: Comparison of determinants of treated unit with Synthetic Control

Variables	Treated Unit	Synthetic Control	Sample Mean
Unemployment	0.087	0.077	0.087
Crime per capita	0.11	0.10	0.12
GDP per capita	33,082	55,935	57,490
Temperature	9.49	9.57	9.98
Sun	134.3	131.03	129.52
Rain	60.45	65.80	65.23
Welterbe	0	0.22	0.27
Kurort	0	0.13	0.09
Bundesgartenschau	0	0.01	0.03
Kueste	0	0.02	0.02
Freizeitpark	0	0.01	0.2
Distance Autobahn	5,440	3,608	2,561
Distance Train	2999	1001	1549
Distance Airport	7,632	10,742	12,215
Overnight stays period 4	1,009,255	1,015,275	1,195,385
Overnight stays period 6	1,024,822	1,020,416	1,216,771
Overnight stays period 8	1,031,995	1,033,804	1,249,554
Overnight stays period 10	1,066,396	1,063,470	1,280,034

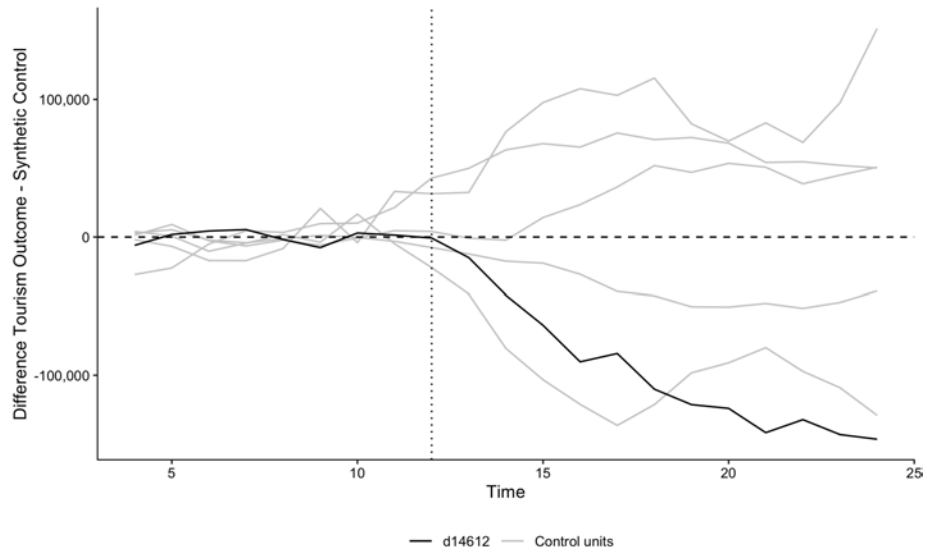
Note: Mean values for treated unit and Synthetic control in the pre-intervention periods.

Table A8: Contribution of units in donor pool

County	Contribution in percentages
Hamburg	0.01
Muenchen	0
Frankfurt am Main	0.01
Koeln	0
Duesseldorf	0
Stuttgart	0.21
Nuernberg	0
Hannover	0
Bremen	0.13
Essen	0.08
Dortmund	0.56

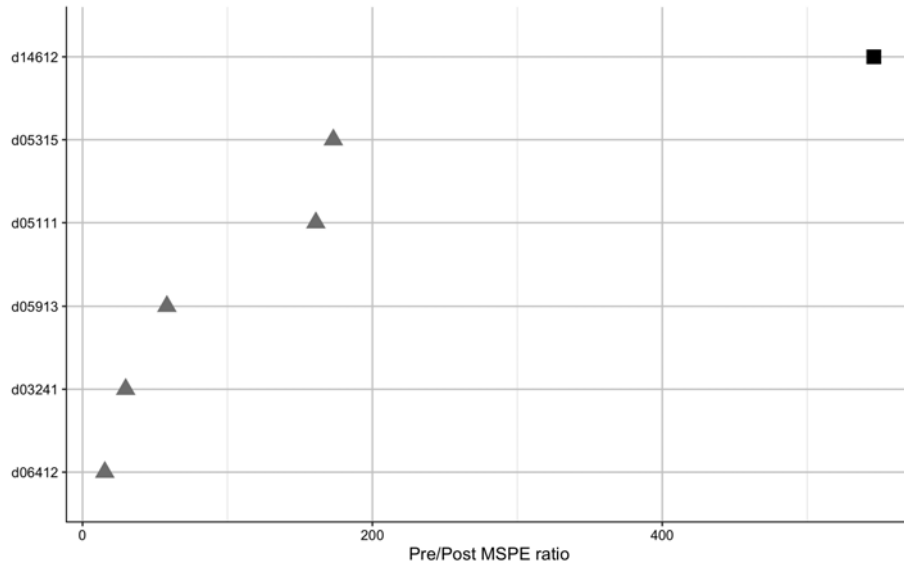
Contribution of units out of the donor pool to the synthetic control of Dresden.

Figure A5: Placebo tests



The figure shows the potential synthetic controls for Dresden (bold) and all comparison units.

Figure A6: Placebo tests



The figure shows the the RSMP for Dresden (d14612) and all comparison units.