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

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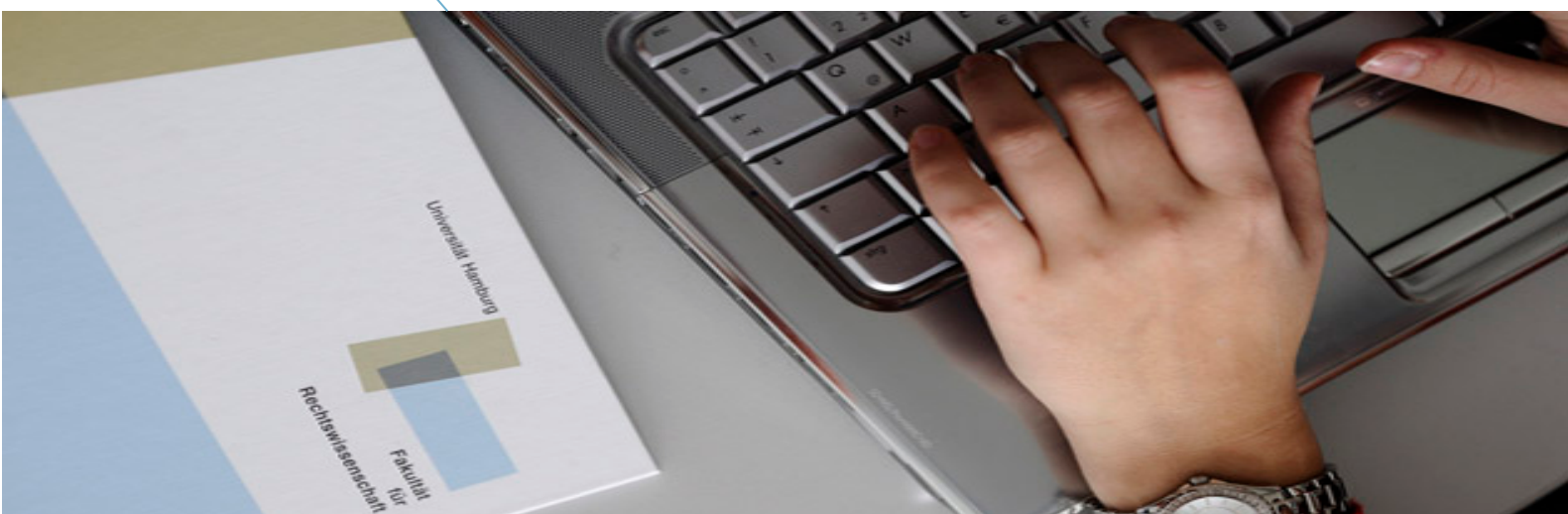
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# The good tourist, the bad refugee and the ugly German: Xenophobic activities and tourism

Marek Endrich  
Stephan Michel

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

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September 10, 2018

## Abstract

Germany shows a more welcoming attitude towards refugees than most other European countries. At the same time, the influx of refugees has led to massive protests, demonstrations and attacks against refugees. We look at the economic effects of these demonstrations and attacks on one important industry, namely tourism. Combining a novel, district-level data set on tourism with data on xenophobic activities, we find that xenophobic demonstrations have negative effects on tourist arrivals. This effect is found for domestic and foreign tourists.

*Keywords:* Xenophobic activities, refugees, tourism, district-level data

*JEL Classification:* F22, L83

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# 1 Introduction

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, are widely covered in the (international) media and put the location in a negative spotlight. For the local economy, this image reduces the attractiveness for tourism.

Tourism is an important part of Germany's economy and accounts for almost 5 percent of the overall economic activity (German Travel Association, 2015). So far, the literature has focused on the effects of terrorism (Neumayer, 2004) or political instability (Saha and Yap, 2014) on tourism. We are interested in another dimension, namely xenophobic activities. As used in this note, these include physical attacks, arson, demonstrations and miscellaneous attacks against refugee housing.

Among the things tourists look for when planning a vacation is the general attractiveness of their destination (Neumayer, 2004). Xenophobic activities reduce this value, and for foreign visitors create the perception of danger to themselves during their stay.

We use a novel district-level data set on tourism in Germany to analyze the effects of xenophobic activities on local tourism. Looking at the sub-national level has the advantage of institutional homogeneity and mitigates omitted variable bias. This research is, to our knowledge, the first that deals with the economic effects of xenophobic activities. We find that xenophobic demonstrations have an adverse effect on tourism. This effect is visible for both domestic and foreign tourists, but foreign tourists respond with a longer delay.

This note can be seen as an addition to the literature on the economics of hate crimes (Gale et al., 2002; Ryan and Leeson, 2011; Mulholland, 2013; Sharma, 2015; Muller and Schwarz, 2018). While the existing literature is concerned with determinants, we focus on the economic effects of xenophobic activities.

# 2 Empirical specification and data

For our analysis of the short-term impact of xenophobic activities on tourism, we focus on the development of tourism in Germany from the fourth quarter

of 2014 to the fourth quarter of 2017. This period coincides with the so-called refugee crisis. We have collected information on tourism for the 401 German districts from the statistical offices of the German states. 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 Städte*). They fulfill policy tasks including education, public transportation and the development of local tourism.

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. The numbers are reported by the guest facilities and we aggregate the data at the quarterly level.<sup>1</sup>

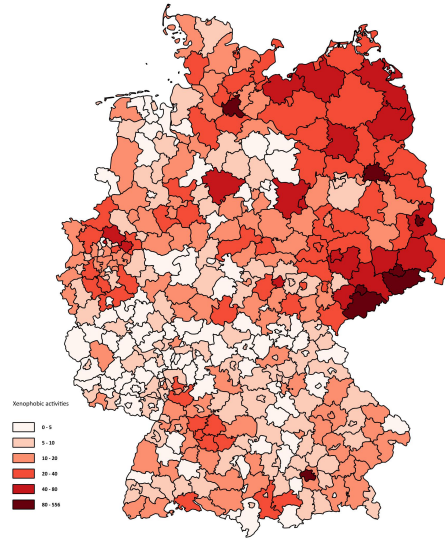
TABLE 1 ABOUT HERE

We relate the development in tourism to incidents of anti-refugee violence in the districts. The NGOs *Amadeu Antonio Stiftung* and *Pro Asyl* keep track of and categorize violence and social unrest aimed at refugees. These activities can be categorized into xenophobic demonstrations, assault, arson attacks, and miscellaneous attacks against refugee housing, and include information on the timing and the location of the events. We extend the dataset gathered by Benček and Strasheim (2016) to the end of 2017 and aggregate it at the quarterly level per district. Our sample includes 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 experienced more xenophobic activities.

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<sup>1</sup>Quarters are defined as January to March, April to June, July to September, and October to December.

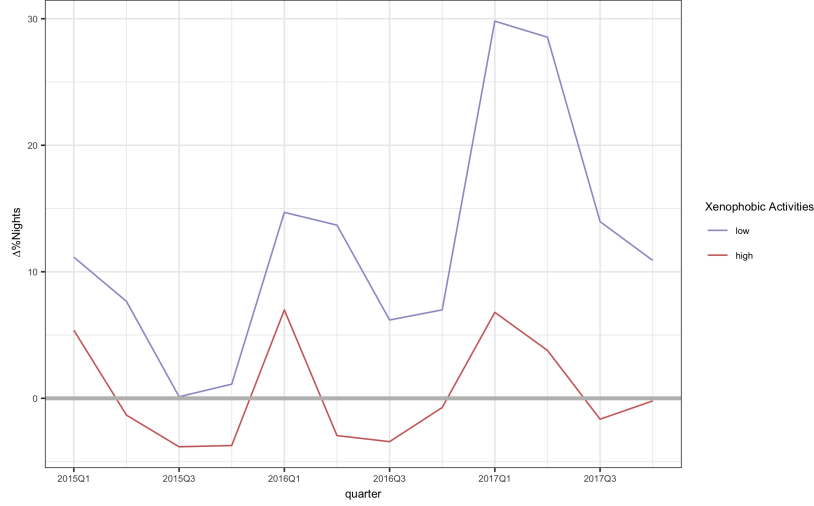
Figure 1: Cases of xenophobic activity



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

Figure 2 shows the percentage change in overnight stays for the 5 districts with the highest overall number of anti-refugee violence, *high*, and the group of 5 districts that exhibit the lowest number of incidents, *low*. Using the quarters of 2014 as the baseline, the growth in tourism in the low districts was consistently above the high districts, and the difference between the two groups increased over time.

Figure 2: High and low violence districts and tourist stays



The respective quarter of 2014 serves as the baseline comparison for each quarter. High level districts are Berlin, Sächsische Schweiz, Dresden Stadt, Chemnitz Stadt, Erzgebirgkreis and low level districts are Grafschaft Bentheim, Weiden in der Oberpfalz, Coburg, Memmingen, Nienburg.

In a next step, we test whether the differences in tourism can be attributed to the varying levels of anti-refugee xenophobic activities. We also take the strong seasonality in tourism data into account. To do this, we estimate the following regression model for the change in overnight stays for district  $d$  by quarter  $q$  in year  $t$ ,

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

where the outcome variable *tourism* is the quarterly percentage change in overnight stays. Subsequent regressions use as the dependent variable overnight stays for foreign and domestic tourists according to their place of residence, 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.

District fixed effects  $v_d$  allow for district specific time trends and net out all time invariant effects that have an effect on the growth rate of tourism. Seasonal fixed effects  $\phi_q$  and year fixed effects  $\delta_t$  control for seasonal trends in tourism and shocks over time. Quarter- year fixed effects  $\phi_q \times \delta_t$  cover for changes in seasonal effects over time, and the inclusion of quarter-state fixed effects  $\phi_q \times \lambda_s$  takes account of different tourism seasons across the states.

The vector  $X'_{d,q,t}$  comprises control variables that may affect tourism demand. We include the first difference of *unemployment*, *crime per capita* and *gdp per capita*,<sup>2</sup> all of which are factors that contribute to the attractiveness of a region for tourism. We add indicators for the presence of a federal or state horticulture show (*Bundesgartenschau* and *Landesgartenschau*) as well as a major sports event (*Sportevent*) in a district as potential tourist attractions.<sup>3</sup> We also 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 stations. This weather data is provided by the German Meteorological Service (*Deutscher Wetterdienst*).

### 3 Results

TABLE 2 and 3 ABOUT HERE

The results from our regressions based on how the different categories of xenophobic activities might impact overnight stays are reported in Table 2. Each of the four columns reports the different categories in turn. 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 roughly one percentage point in the first and by another percentage point in the second quarter after the incident. The impact is statistically strongest in the second quarter after the

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<sup>2</sup>The 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.

<sup>3</sup>*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.



incidents, which is in line with the expected delay in the reaction of tourists. Regarding the temporal dimension of the effect, we find a significant effect for a partial reversion after four quarters. We do not observe a significant change in tourism as a reaction to the 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. Assuming that demonstrations gain more attention in the media than the other categories makes our result plausible and hints at media outlets as a key transmission channel.

In Column 1 and 2 of Table 3 we separately 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 mainly driven by a decrease in the number of arrivals and not by a shorter duration of trips. Tourists refrain from visiting a district that exhibits a high number of xenophobic activities, while the average duration of the remaining trips stays the same.

## 4 Conclusion

To sum up, we have shown that demonstrations against refugees have a negative impact on tourist arrivals. This finding highlights an economic externality of xenophobic activities that has not been discussed in the literature so far. Our estimate is certainly 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 also has repercussion on potential investors and workers.

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Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Nights_domestic	5,184	226,462	384,002	5,825	4,762,345
Nights_foreign	5,184	49,768	211,430	284	4,309,604
Arrivals_domestic	5,178	84,423	147,748	3,731	2,133,668
Arrivals_foreign	5,178	22,075	85,538	82	1,520,044
Arrivals	5,178	106,499	226,797	4,457	3,587,795
Nights	5,184	276,230	552,959	7,771	8,975,984
cases	5,187	1.272	3.495	0	115
miscellaneous_attack	5,187	0.910	2.522	0	88
arson	5,187	0.052	0.298	0	9
assault	5,187	0.187	0.704	0	14
demonstration	5,187	0.082	0.668	0	23
rain	5,187	62.964	23.935	24.215	190.321
sun	5,187	131.458	65.820	33.016	255.949
temperature	5,187	9.612	5.542	0.377	19.403
Duration	5,178	2.601	0.869	1.413	7.420
Duration_foreign	5,178	2.432	0.764	1.255	11.667
Duration_domestic	5,178	2.616	0.917	1.397	7.542
crimepc	5,187	0.061	0.026	0.022	0.160
gdppc	5,187	35,124	14,694	14,932	138,664
pop	5,187	204,701	237,776	34,048	3,584,326
Bundesgartenschau	5,187	0.002	0.040	0	1
Landesgartenschau	5,187	0.005	0.065	0	1
Sportevent	5,187	0.001	0.022	0	1
unemp	5,187	0.057	0.027	0.011	0.163

Table 2: Effect of xenophobic activities on overnight stays

	<i>Dependent variable:</i>			
	(Growth_nights)			
	(1)	(2)	(3)	(4)
lag(Growth_miscellaneous_attack, 1)	−0.001 (0.002)			
lag(Growth_miscellaneous_attack, 2)	0.003 (0.002)			
lag(Growth_miscellaneous_attack, 3)	0.0003 (0.002)			
lag(Growth_miscellaneous_attack, 4)	0.001 (0.002)			
lag(Growth_assault, 1)		0.001 (0.005)		
lag(Growth_assault, 2)		0.0002 (0.006)		
lag(Growth_assault, 3)		0.002 (0.006)		
lag(Growth_assault, 4)		−0.002 (0.007)		
lag(Growth_arson, 1)			−0.002 (0.008)	
lag(Growth_arson, 2)			−0.011 (0.011)	
lag(Growth_arson, 3)			−0.007 (0.014)	
lag(Growth_arson, 4)			−0.008 (0.012)	
lag(Growth_demonstration, 1)				−0.009* (0.005)
lag(Growth_demonstration, 2)				−0.010*** (0.004)
lag(Growth_demonstration, 3)				−0.004 (0.005)
lag(Growth_demonstration, 4)				0.008** (0.004)
District Fixed Effects	Yes	Yes	Yes	Yes
Seasonal Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	Yes	Yes	Yes	Yes
Quarter-State Fixed Effects	Yes	Yes	Yes	Yes
District-level controls	Yes	Yes	Yes	Yes
Observations	3,589	3,589	3,589	3,589
R <sup>2</sup>	0.257	0.256	0.256	0.257
Adjusted R <sup>2</sup>	0.147	0.146	0.146	0.147
F Statistic (df = 58; 3124)	18.636***	18.551***	18.566***	18.646***

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;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 3: Effect of xenophobic activities on locals versus foreigners and on number of stays versus duration of stay

	<i>Dependent variable:</i>			
	(Growth_nights_domestic)	(Growth_nights_foreign)	(Growth_arrivals)	(Growth_duration)
	(1)	(2)	(3)	(4)
lag(Growth_demonstration, 1)	−0.010** (0.005)	−0.005 (0.010)	−0.012** (0.005)	0.001 (0.003)
lag(Growth_demonstration, 2)	−0.011** (0.004)	−0.023** (0.010)	−0.012** (0.005)	0.001 (0.002)
lag(Growth_demonstration, 3)	−0.006 (0.005)	−0.018 (0.012)	−0.007 (0.006)	0.004 (0.003)
lag(Growth_demonstration, 4)	0.008* (0.004)	0.002 (0.007)	0.008* (0.004)	0.001 (0.002)
District Fixed Effects	Yes	Yes	Yes	Yes
Seasonal Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Quarter-Year Fixed Effects	Yes	Yes	Yes	Yes
Quarter-State Fixed Effects	Yes	Yes	Yes	Yes
District-level controls	Yes	Yes	Yes	Yes
Observations	3,589	3,589	3,581	3,581
R <sup>2</sup>	0.252	0.206	0.269	0.120
Adjusted R <sup>2</sup>	0.140	0.088	0.160	−0.011
F Statistic	18.106*** (df = 58; 3124)	13.953*** (df = 58; 3124)	19.746*** (df = 58; 3116)	7.333*** (df = 58; 3116)

*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 4: Table 2 with controls coefficients

	<i>Dependent variable:</i>			
	(Growth_ueb)			
	(1)	(2)	(3)	(4)
lag(Growth_unemp, 1)	4.456*	4.426*	4.437*	4.424*
	(2.575)	(2.570)	(2.563)	(2.560)
lag(Growth_crimepc, 1)	0.134	0.138	0.130	0.118
	(0.155)	(0.155)	(0.154)	(0.154)
lag(Growth_gdppc, 1)	-0.776	-0.822	-0.795	-0.797
	(1.381)	(1.387)	(1.388)	(1.387)
Growth_sport	0.040	0.050	0.050	0.068
	(0.097)	(0.101)	(0.100)	(0.109)
Growth_landesgs	-0.056	-0.057	-0.057	-0.058
	(0.063)	(0.063)	(0.063)	(0.063)
Growth_bundesgs	0.224*	0.217*	0.234*	0.204*
	(0.119)	(0.123)	(0.121)	(0.122)
lag(growth_temperature, 1)	-0.020*	-0.020*	-0.019*	-0.020*
	(0.010)	(0.010)	(0.010)	(0.010)
lag(growth_sun, 1)	-0.0002	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
lag(growth_rain, 1)	0.0001	0.00004	0.00004	0.00004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
lag(Growth_miscellaneous_attack, 1)	-0.001			
	(0.002)			
lag(Growth_miscellaneous_attack, 2)	0.003			
	(0.002)			
lag(Growth_miscellaneous_attack, 3)	0.0003			
	(0.002)			
lag(Growth_miscellaneous_attack, 4)	0.001			
	(0.002)			
lag(Growth_assault, 1)		0.001		
		(0.005)		
lag(Growth_assault, 2)		0.0002		
		(0.006)		
lag(Growth_assault, 3)		0.002		
		(0.006)		
lag(Growth_assault, 4)		-0.002		
		(0.007)		
lag(Growth_arson, 1)			-0.002	
			(0.008)	
lag(Growth_arson, 2)			-0.011	
			(0.011)	
lag(Growth_arson, 3)			-0.007	
			(0.014)	
lag(Growth_arson, 4)			-0.008	
			(0.012)	
lag(Growth_demonstration, 1)				-0.009*
				(0.005)
lag(Growth_demonstration, 2)				-0.010***
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lag(Growth_demonstration, 3)				-0.004
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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 5: Table 3 with controls coefficients

	<i>Dependent variable:</i>			
	(Growth_ueb_in)	(Growth_ueb_aus)	(Growth_ank)	(Growth_dauer)
	(1)	(2)	(3)	(4)
lag(Growth_unemp, 1)	4.034 (2.615)	7.594 (4.662)	7.763*** (2.516)	−2.296*** (0.465)
lag(Growth_crimepc, 1)	0.135 (0.159)	0.256 (0.301)	0.151 (0.135)	−0.037 (0.051)
lag(Growth_gdppc, 1)	−0.933 (1.388)	−0.311 (2.240)	−0.417 (1.192)	−0.031 (0.367)
Growth_sport	0.071 (0.105)	0.120 (0.131)	−0.023 (0.120)	0.072* (0.040)
Growth_landesgs	−0.042 (0.065)	−0.180 (0.114)	−0.067 (0.053)	0.007 (0.026)
Growth_bundesgs	0.235* (0.124)	−0.197 (0.135)	0.172* (0.102)	0.053 (0.041)
lag(growth_temperature, 1)	−0.019* (0.011)	−0.034** (0.016)	−0.017* (0.009)	−0.004 (0.003)
lag(growth_sun, 1)	−0.0001 (0.0002)	−0.001 (0.0004)	−0.0001 (0.0002)	−0.00004 (0.0001)
lag(growth_rain, 1)	0.00001 (0.0002)	−0.001** (0.0003)	0.00002 (0.0002)	−0.00003 (0.0001)
lag(Growth_demonstration, 1)	−0.010** (0.005)	−0.005 (0.010)	−0.012** (0.005)	0.001 (0.003)
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