Online Appendix for “Trade Layoffs and Hate in the United States”

Contents

A Descriptive statistics

Table 3: Descriptive statistics for key variables

Statistic	N	Mean	St. Dev.	Min	Median	Max
log(Hate incidents + 1)	46,895	0.115	0.423	0	0	5
Number of hate groups	46,895	0.067	0.372	0	0	13
Trade layoffs	46,895	0.371	1.930	0	0	89
Population (log, interpolated)	46,880	10.268	1.459	4.315	10.159	16.102
Nighttime luminosity	46,880	8.739	10.317	0.000	5.663	63.000
Percent white population	43,680	86.138	16.101	8.875	93.072	100.000
Percent voting Republican in most recent election	46,529	59.365	14.026	4.087	60.144	96.033
Unemployment rate	46,833	6.447	2.778	1.100	5.800	28.900

The complete list of unique causes listed in the trade layoff data are: *Certified Upstream; Certified - No Description; Imports; Shift in Production; High and rising aggregate U.S. imports from Canada/Mexico; Increased customer imports from Canada/Mexico, both countries; Increased customer imports from Canada; Shift in production to Mexico; Increased company imports from Mexico; Certified Downstream; Increased company imports from Canada/Mexico, both countries; Increased company imports from Canada; Shift in production to Canada; and Increased customer imports from Mexico.*

B Correlation matrix for independent variables

Table 4: Correlations between key independent variables

	Trade layoffs	Population	Nighttime light	Pct. white	Unemployment rate	Pct. Republican
Trade layoffs	1	0.284	0.257	-0.053	0.042	-0.136
Population	0.284	1	0.688	-0.172	0.086	-0.392
Nighttime light	0.257	0.688	1	-0.198	-0.021	-0.352
Pct. white	-0.053	-0.172	-0.198	1	-0.279	0.425
Unemployment rate	0.042	0.086	-0.021	-0.279	1	-0.271
Pct. Republican	-0.136	-0.392	-0.352	0.425	-0.271	1

C Including all types of hate groups in the dependent variable

The list below documents all of the hate groups include

- **Anti-immigrant**
- Anti-LGBT
- **Anti-Muslim**
- Black Nationalist
- Christian Identity
- General Hate
- Hate Music
- Holocaust Denial
- **Identity**
- Ku Klux Klan
- Neo-Confederate
- **Neo-Nazi**
- **Neo-Volkisch**
- Other
- Racist Skinhead
- Radical Catholicism
- **White Nationalist**

Table 5: Hate group (all types) presence and trade layoffs

	DV: Number of hate groups (all types) present in county	
	(1)	(2)
Trade layoffs$_{t-1}$	0.0166***	0.0019**
	(0.0011)	(0.0010)
Population (log, interpolated)	0.0182***	0.1234
	(0.0021)	(0.1203)
Nighttime luminosity	0.0020***	$-$0.0017*
	(0.0003)	(0.0010)
Percent white population	$-$0.0005**	$-$0.0040
	(0.0002)	(0.0066)
Unemployment rate	$-$0.0021**	0.0017
	(0.0010)	(0.0024)
Percent voting Republican in most recent election	$-$0.0004**	$-$0.0018*
	(0.0002)	(0.0009)
County FEs	N	Y
N. counties	3097	3097
Observations	40,247	37,150

*p<0.1; **p<0.05; ***p<0.01
Note: Panel regression models.
Panel-corrected standard errors in parentheses.
Year dummies and lagged (1-period) outcome included in all models.
State dummies included in Model 1.

D Details of coding precision issues

Google returns the geometric center of territorial boundaries. Although this provides precise coordinates for each city, some cities are spread across multiple counties. Thus, there is the possibility of some county-level measurement error. Absent information about the spatial boundaries of *cities* – rather than *counties* – this is, unfortunately, an unavoidable issue. This could lead to overestimating or underestimating hate-group activity within counties. For example, the SPLC may identify a group in city X that spans multiple counties, Y and Z, without identifying a particular county. When the `geocode` function returns coordinates for a place name, those coordinates will correspond to a single county, say Y. But, if the activities of that group in city X are primarily in county Z, I will have mis-measured the activity of that group. While this introduces error into the analysis, it is relatively rare, as only about 3.3% of incorporated areas in the United States are located in multiple counties. According to `Statista.com`, which summarizes information from the United States Census Bureau, there were 19,505 incorporated places (cities, towns, villages) in the United States in 2015. Source: `https://www.statista.com/statistics/241695/number-of-us-cities-towns-villages-by-population-size/` (Accessed June 12, 2018). As of June 12, 2018, the Wikipedia page for "List of U.S. municipalities in multiple counties" lists 644 cities, towns, or municipalities that are located in multiple counties. Source: `https://en.wikipedia.org/wiki/List_of_U.S._municipalities_in_multiple_counties` (Accessed June 12, 2018).

E Alternative measure of trade vulnerability

In the main text I use a measure of trade-related layoffs as the key independent variable. While that measure fits well with the theoretical emphasis on observable trade impacts influencing hate activity, it does not allow for answering the question of whether perceived vulnerability to trade competition acts independently of actual layoffs. Although testing that mechanism is not essential to theory, it is a question with great practical importance.

To generate a measure of *import competition vulnerability* similar to that used by Autor, Dorn and Hanson (2013) and Colantone and Stanig (2018) I use data on the total number of employees registered in each US county in each industry-group level (6 digit NAICS code) as recorded by the US Bureau of Labor Statistics (US Bureau of Labor Statistics 2018). The data are provided in quarter-years with employment level data for each month of a quarter for each industry-group. Thus, each year has 12 data points (at most) of a count of employees in each industry-group. I take the average of available values for each year to obtain the average number of employees in each industry-group. For simplicity I refer to this as the number of employees in each industry group, noting here that it is actually a monthly average within years.

With that data, I use various measures to estimate the import shock as follows: Number of employees in county i in year t (L_i); Number of employees in county i in industry group k in year t (L_{ik}); Number of employees in industry group k across all counties in year t (L_k); and total imports. To construct this measure I use data from the United States' Census Bureau's USA Trade Online database (United States Census Bureau 2018) and count all "General imports" to the United States.[21] This data base reports total imports aggregated to various levels of the NAICS coding scheme. I use the 6-digit NAICS level to match with the county-level employment data. Using these measures, I follow Colantone and Stanig (2018, 204) to generate a measure of import shock in county i in year t equivalent to

$$\text{Import Shock}_{it} = \sum_k \frac{L_{ik(2000)}}{L_{i(2000)}} * \frac{\Delta\text{Imports}_{kt}}{L_{k(2000)}}$$

This measure can be interpreted as the growth in imports (in thousands of 2005 dollars) per US worker during a given year. For locales with workforces that are similar (dissimilar) to the distribution of imports, the import competition measure is higher (lower). So that the measure is not unduly sensitive to short-term fluctuations, I take the average of the values of the "shock" for the three-year period preceding the current year. I create one measure for all imports and one that only counts imports from China.

Table 6 reports the results of the analysis when substituting this measure for the measure of trade-related job losses. Unlike in the main text, here I find no evidence that import vulnerability in terms of sector similarity to imports is associated with hate for both the measure of all imports and Chinese imports only.

Table 6: Hate crimes, hate groups, and import competition

	Dependent variable:			
	Hate crimes	Hate groups	Hate crimes	Hate groups
	(1)	(2)	(3)	(4)
Import shock$_{\text{3-year avg.}}$	0.00005	0.0002		
	(0.0005)	(0.0004)		
China shock$_{\text{3-year avg.}}$			0.010	0.0002
			(0.018)	(0.016)
Population (log, interpolated)	−0.135	−0.115	−0.135	−0.115
	(0.118)	(0.104)	(0.118)	(0.104)
Nighttime luminosity	0.004***	−0.003***	0.004***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Percent white population	0.005	0.005	0.005	0.005
	(0.005)	(0.005)	(0.005)	(0.005)
Unemployment rate	−0.003*	0.001	−0.003*	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Percent voting Republican in most recent election	0.0002	−0.001**	0.0002	−0.001**
	(0.001)	(0.0005)	(0.001)	(0.0005)
Observations	30,956	30,956	30,956	30,956

*p<0.1; **p<0.05; ***p<0.01
Note: Estimated standard errors in parentheses.
Year dummies and lagged (1-period) outcome included in all models.

F Mexico-related trade layoffs and anti-Hispanic hate crimes

Table 7: Anti-Hispanic hate crime incidents and Mexican import competition

	Dependent variable:			
	Incidents involving anti-Hispanic bias		Incidents with exclusively anti-Hispanic bias	
	(1)	(2)	(3)	(4)
Trade layoffs attributed to Mexico	0.2534^{***}	-0.0116	0.2538^{***}	-0.0117
	(0.0735)	(0.0609)	(0.0734)	(0.0607)
Population (log, interpolated)	0.0277^{***}	-0.0884	0.0277^{***}	-0.0864
	(0.0037)	(0.0971)	(0.0037)	(0.0973)
Nighttime luminosity	0.0021^{***}	0.0146^{***}	0.0021^{***}	0.0147^{***}
	(0.0005)	(0.0019)	(0.0005)	(0.0019)
Percent white population	-0.0005	0.0022	-0.0004	0.0021
	(0.0004)	(0.0062)	(0.0004)	(0.0062)
Unemployment rate	-0.0049^{***}	-0.0037	-0.0049^{***}	-0.0036
	(0.0016)	(0.0032)	(0.0016)	(0.0032)
Percent voting Republican in most recent election	-0.0002	0.0032^{***}	-0.0002	0.0034^{***}
	(0.0004)	(0.0011)	(0.0004)	(0.0011)
County FEs	N	Y	N	Y
N. counties	3097	3097	3097	3097
Observations	40,247	40,247	40,247	40,247

*p<0.1; **p<0.05; ***p<0.01
Note: Panel regression models.
Panel-corrected standard errors in parentheses.
Year dummies and lagged (1-period) outcome included in all models.
State dummies included in Models 1 and 3

G Alternative measure of trade vulnerability (China only)

There may be some degree of noise in the data used in Section E above. It may be unreasonable to expect an overall trade vulnerability to correlate with all types of hate crimes, even if the analysis is limited to those involving "foreign" groups. To provide a more direct test of the import vulnerability-hate relationship, I subset the import data to only include Chinese imports and subset the hate crime data to include only cases are recorded as having been motivated by an "Anti-Asian" bias. China is one of the most visible players in international trade, and "import competition from China, which surged after 2000, was a major force behind both recent reductions in US manufacturing employment and ...weak overall US job growth" (Acemoglu et al. 2016, S141). Because some incidents have multiple motivations, I include two separate measures. In the first, I count all incidents that include list an "Anti-Asian" bias whether or not other motivations are also included. In the second, I limit the measure to incidents that were motivated purely by Anti-Asian bias with no other motive. While including all "Anti-Asian" incidents encompasses a broader set of incidents that not necessarily connected to Chinese competition, per se, it is certainly a less noisy measure than using all hate crime incidents.[22] The use of data only on imports from China follows other recent work on import shocks (e.g., Autor, Dorn and Hanson 2013; Colantone and Stanig 2018). Further, employers routinely cite Chinese competition when publicly justifying decisions to close operations. For example, the solar panel company Evergreen Solar laid off 800 workers in Massachusetts in 2011 "in response to plunging prices for solar panels" due to the "much higher government support available [for producing solar panels] in China" (Bradsher 2011).

I report the results of this analysis in Table 8 below. The results mirror those reported in Table 6. Although the estimated coefficients on the measure of Chinese import vulnerability are always positive, they are only close to being statistically significant in the models that exclude county-fixed effects (Models 1 and 3). Though there is arguably a closer connection between the measure of economic vulnerability and its (potential) relationship with political hate crime in these models, there is still only weak evidence for an import vulnerability-hate link.

Table 8: Anti-Asian hate crime incidents and Chinese import competition

	Dependent variable:			
	Incidents involving anti-Asian bias		Incidents with exclusively anti-Asian bias	
	(1)	(2)	(3)	(4)
China import vulnerability$_{\text{3-year avg.}}$	0.0219*	0.0104	0.0221*	0.0105
	(0.0127)	(0.0206)	(0.0127)	(0.0205)
Population (log, interpolated)	0.0103***	$-$0.0521	0.0104***	$-$0.0470
	(0.0018)	(0.1372)	(0.0018)	(0.1370)
Nighttime luminosity	0.0022***	0.0013*	0.0021***	0.0013
	(0.0003)	(0.0008)	(0.0003)	(0.0008)
Percent white population	$-$0.0006***	0.0059	$-$0.0006***	0.0058
	(0.0002)	(0.0064)	(0.0002)	(0.0063)
Unemployment rate	$-$0.0040***	$-$0.0024	$-$0.0039***	$-$0.0023
	(0.0009)	(0.0018)	(0.0009)	(0.0018)
Percent voting Republican in most recent election	$-$0.0003	0.0002	$-$0.0003	0.0002
	(0.0002)	(0.0006)	(0.0002)	(0.0006)
County FEs	N	Y	N	Y
N. counties	3097	3097	3097	3097
Observations	34,053	30,956	34,053	30,956

*p<0.1; **p<0.05; ***p<0.01
Note: Panel regression models.
Estimated standard errors in parentheses.
Year dummies and lagged (1-period) outcome included in all models.
State dummies included in Models 1 and 3.
Temporal domain: 2006-2017.

H Alternative measure: Trade layoffs as percent of labor force

Table 9: Trade layoffs as a percent of the labor force

	Dependent variable:			
	Hate crimes		Hate groups	
	(1)	(2)	(3)	(4)
Trade layoffs as percent of labor force	0.0015	0.0015	0.0001	0.00002
	(0.0023)	(0.0018)	(0.0020)	(0.0016)
Population (log, interpolated)	0.0291^{***}	0.0027	0.0108^{***}	0.1401^{**}
	(0.0020)	(0.0596)	(0.0013)	(0.0684)
Nighttime luminosity	0.0033^{***}	0.0036^{***}	0.0016^{***}	-0.0022^{***}
	(0.0003)	(0.0007)	(0.0002)	(0.0006)
Percent white population	-0.0006^{***}	0.0005	-0.0002	-0.0005
	(0.0002)	(0.0040)	(0.0001)	(0.0039)
Unemployment rate	-0.0049^{***}	-0.0023	-0.0016^{**}	-0.0001
	(0.0008)	(0.0016)	(0.0007)	(0.0014)
Percent voting Republican in most recent election	-0.0004^{**}	0.0003	-0.0003^{**}	-0.0010^{*}
	(0.0002)	(0.0006)	(0.0001)	(0.0005)
County FEs	N	Y	N	Y
N. counties	3097	3097	3097	3097
Observations	40,247	37,150	40,247	37,150

*p<0.1; **p<0.05; ***p<0.01
Note: Panel regression models.
Panel-corrected standard errors in parentheses.
Year dummies and lagged (1-period) outcome included in all models.
State dummies included in Models 1 and 3.

I Limiting the sample to pre-2014

Table 10: Pre-2014 models

	Dependent variable:	
	Hate crimes	Hate groups
	(1)	(2)
Trade layoffs	0.0002	0.0006
	(0.0007)	(0.0006)
Population (log, interpolated)	-0.0590	0.2778^{***}
	(0.0702)	(0.0865)
Nighttime luminosity	0.0040^{***}	-0.0016^{**}
	(0.0007)	(0.0006)
Percent white population	-0.0010	-0.0011
	(0.0046)	(0.0044)
Unemployment rate	-0.0026	-0.0005
	(0.0018)	(0.0016)
Percent voting Republican in most recent election	0.0009	0.0009
	(0.0008)	(0.0007)
County FEs	Y	Y
N. counties	3097	3097
Observations	27,859	27,859

*p<0.1; **p<0.05; ***p<0.01
Note: Panel regression models.
Panel-corrected standard errors in parentheses.
Year dummies and lagged (1-period) outcome included in all models.

J Alternative measure: level of white population

Table 11: Conditioning effects of changing demographics

	Dependent variable:	
	Hate crimes	Hate groups
	(1)	(2)
Trade layoffs$_{t-1}$	-0.005	0.014^{***}
	(0.004)	(0.004)
Percent white population$_{t-1}$	0.005^{**}	0.004^{**}
	(0.002)	(0.002)
Population (log, interpolated)	-0.062^{*}	0.001
	(0.032)	(0.033)
Nighttime luminosity$_{t-1}$	0.009^{***}	0.0002
	(0.001)	(0.001)
Change in unemployment rate from $t-1$	-0.001	-0.0003
	(0.001)	(0.001)
Percent voting Republican in most recent election	0.001^{***}	0.00003
	(0.0004)	(0.0004)
Trade layoffs $\times$ Percent white population$_{t-1}$	0.0001	-0.0001^{***}
	(0.0001)	(0.0001)
County FEs	Y	Y
N. counties	3097	3097
Observations	40,247	40,247

*p<0.1; **p<0.05; ***p<0.01
Note: Panel regression models.
Panel-corrected standard errors in parentheses.
Year dummies and lagged (1-period) outcome included in all models.

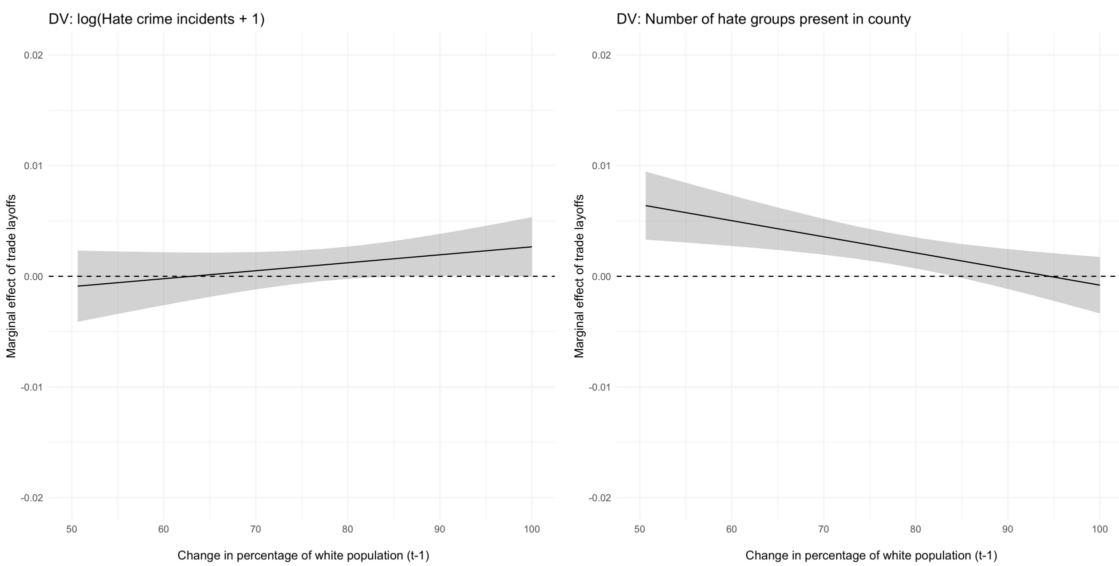

Figure 2: Relationship between trade layoffs, white population, and hate activity

K Alternative model specification: Generalized method of moments estimation

Table 12: Generalized Method of Moments estimation

	Dependent variable:	
	Hate crimes	Hate groups
	(1)	(2)
Trade layoffs	-0.0001	0.004^{**}
	(0.002)	(0.002)
Population (log, interpolated)	0.009	0.016
	(0.057)	(0.052)
Nighttime luminosity	0.008^{***}	0.0005
	(0.002)	(0.002)
Percent white population	-0.001	0.002
	(0.003)	(0.003)
Unemployment rate	-0.0004	0.001
	(0.001)	(0.001)
Percent voting Republican in most recent election	0.001^{*}	0.0004
	(0.001)	(0.001)
Lagged hate crimes (1-period)	0.104^{***}	
	(0.020)	
Lagged hate groups (1-period)		0.616^{***}
		(0.050)
Observations	3,097	3,097

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

L Alternative dependent variable: Anti-LGBT groups

Table 13: Hate group (Anti-LGBT focus) presence and trade layoffs

	DV: Number of hate groups (Anti-LGBT focus) present in county	
	(1)	(2)
Trade layoffs$_{t-1}$	0.0008***	-0.0001
	(0.0001)	(0.0002)
Population (log, interpolated)	-0.0007^{**}	0.0077
	(0.0003)	(0.0072)
Nighttime luminosity$_{t-1}$	-0.0006^{***}	-0.0012^{***}
	(0.0001)	(0.0002)
Change in percent white population$_{t-1}$	0.0010	0.0013
	(0.0009)	(0.0012)
Change in unemployment from $t-1$	-0.0003	-0.0001
	(0.0003)	(0.0003)
Percent voting Republican in most recent election	0.00004	-0.0001^{*}
	(0.00002)	(0.0001)
GDP estimate (2006)	0.0162***	
	(0.0015)	
Travel time to major cities	0.0014*	
	(0.0008)	
County FEs	N	Y
N. counties	3097	3097
Observations	40,240	40,240

*p<0.1; **p<0.05; ***p<0.01
Note: Panel regression models.
Panel-corrected standard errors in parentheses.
Year dummies and lagged (1-period) outcome included in all models.
State dummies included in Model 1.

M Alternative conditioning variable: Change in percent of Asian population

Table 14: Conditioning effects of changing demographics

	Dependent variable:	
	Hate crimes	Hate groups
	(1)	(2)
Trade layoffs	0.0005	0.003***
	(0.001)	(0.001)
Change in percent Asian population	0.041**	0.017
	(0.021)	(0.022)
Population (log, interpolated)	$-$0.066**	$-$0.008
	(0.032)	(0.033)
Nighttime luminosity	0.009***	0.0005
	(0.001)	(0.001)
Unemployment rate	$-$0.0003	$-$0.001
	(0.001)	(0.001)
Percent voting Republican in most recent election	0.002***	0.0002
	(0.0004)	(0.0004)
Trade layoffs $\times$ Change in percent Asian population	0.007	$-$0.004
	(0.006)	(0.006)
County FEs	Y	Y
N. counties	3097	3097
Observations	40,247	40,247

*p<0.1; **p<0.05; ***p<0.01
Note: Panel regression models.
Panel-corrected standard errors in parentheses.
Year dummies and lagged (1-period) outcome included in all models.

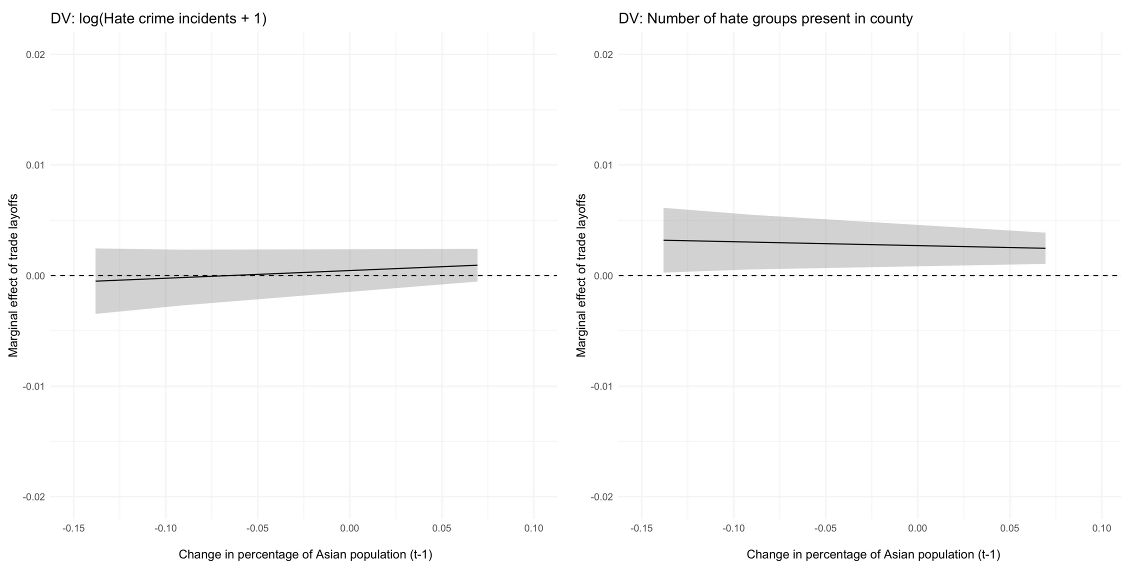

Figure 3: Relationship between trade layoffs, changing in percentage of local Asian population, and hate activity

N Extra time-invariant controls for local GDP and distance to major cities

In this section I include two variables that are measured at the county-level but do not vary over time. The first time-invariant county-level measure I include is an estimate of gross domestic product based on activity in the year 2006 from Ghosh et al. (2010). Counties with greater levels of economic activity may be more vulnerable to import competition, and levels of economic output may be correlated with incidents of hate crimes and the presence of hate groups. These county-level estimates are available only for the year 2006. Second, I include a measure of travel time (in minutes) to major cities from Nelson (2008). Proximity to major cities may be correlated with urban versus rural status which may influence import vulnerability. Counties further from major cities may be less exposed and less accepting of individuals from different backgrounds. This data comes from Goodman et al. (2019).

Table 15: Hate crimes, hate groups, and trade layoffs (extra controls)

	Dependent variable:	
	Hate crimes	Hate groups
	(1)	(2)
Trade layoffs	0.014***	0.008***
	(0.001)	(0.001)
Population (log, interpolated)	0.013***	0.002
	(0.002)	(0.001)
Nighttime luminosity	−0.002***	−0.001***
	(0.0004)	(0.0004)
Percent white population	−0.0004***	−0.0001
	(0.0001)	(0.0001)
Unemployment rate	−0.005***	−0.001**
	(0.001)	(0.001)
Percent voting Republican in most recent election	−0.0003**	−0.0002*
	(0.0001)	(0.0001)
GDP estimate (2006)	0.139***	0.066***
	(0.008)	(0.006)
Travel time to major cities	0.038***	0.018***
	(0.004)	(0.003)
Observations	40,247	40,247

*p<0.1; **p<0.05; ***p<0.01
Note: Panel-corrected standard errors in parentheses.
Year and state dummies and lagged (1-period) outcome included in all models.

References

Ghosh, Tilottama, Rebecca L Powell, Christopher D Elvidge, Kimberly E Baugh, Paul C Sutton and Sharolyn Anderson. 2010. "Shedding light on the global distribution of economic activity." *The Open Geography Journal* 3(1).

Nelson, Andrew. 2008. "Estimated travel time to the nearest city of 50,000 or more people in year 2000." *Ispra, Italy*.