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The Impact of Import Competition and Trump's Election on Hate Crimes

by

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Abstract

The United States experienced a marked increase in hate crimes following the 2016 presidential election. This paper examines how Chinese import competition, combined with the political climate following Trump's election, affected hate crimes. I found that Trump's election led to more hate crimes in areas more exposed to import competition, with a larger effect on predominantly White communities. Further, the nature of the crimes varied in different racial communities: hate crimes in White areas were mostly racially motivated, whereas they were non-racially motivated in other areas. The mechanisms driving these patterns varied as well: social factors such as online racism were the main drivers in White areas, while economic factors such as the unemployment rate were the main drivers in other areas.

JEL: F1 – Empirical Studies of Trade; K4 – Legal Procedure, the Legal System, and Illegal Behavior; P4 – Other Political Systems

1. INTRODUCTION

Hate crimes, defined as criminal acts motivated by prejudice based on race, gender, religion, disability, sexual orientation, or ethnicity (*Hate Crime Statistics*, 2022), present unique challenges to society and policymakers. Such criminal behaviors are fundamentally different from other criminal activities, often involving offenders who do not know their victims personally and are driven by a desire to do harm, even at the offender's own expense (Gale et al., 2002). These crimes are not only harmful to individuals but also destabilize communities, fostering fear and division (Iganski, 2001; Sganga, 2021; Williamson & Gelfand, 2019).

Understanding the socio-economic and political factors behind hate crimes is critical for developing effective policies to combat them. Previous research has identified various contributing factors such as labor market competition, unemployment, income inequality, social identity, and political rhetoric (Basu, 2021; DiLorenzo, 2021; Dipoppa et al., 2023; Green et al., 1998; Lyons, 2008; Pinderhughes, 1993; Souza et al., 2022; White & Perrone, 2001).

Historical events and political changes have played a significant role in shaping hate crime patterns, as seen in the United States. In the US, FBI data show three sudden changes in hate crimes: one following the September 11 attacks in 2001, one after Donald Trump's 2016 election (Williamson & Gelfand, 2019), and the last one in 2020, which is mostly attributed to the coronavirus outbreak (Sganga, 2021).

A significant economic shock that may influence hate crimes is import competition, particularly from China. China, as the most important exporter to the US, accounts for 89% of the growth in US imports from low-income countries since 2000 (Autor et al., 2013). The expansion in import competition from China has been associated with substantial economic losses and has triggered various social and political responses in high-income countries such as the US. These include increased nationalism (McManus & Schaur, 2016), negative media representation of China (Lu et al., 2018), greater support for far-right parties (Autor et al., 2020; Colantone & Stanig, 2018), and reduced support for free trade policies (Feigenbaum & Hall, 2015).

The election of Donald Trump in 2016 marked another pivotal factor in recent socio-economic changes. During his campaign, he promoted xenophobic ideologies and blamed migrants and imports for negative social and economic consequences (Fritze, 2019; Haberman, 2016). Multiple hate crime reports documented offenders explicitly referencing Trump's rhetoric

(Kyle Scott Clauss, 2016; Lindsey Bever, 2017), and multiple studies link his tweets to hate crimes (Cao et al., 2023; Müller & Schwarz, 2021).

In this paper, I study how local import competition combined with the political climate following Donald Trump's election in 2016 led to a surge in hate crimes in the United States. Specifically, I examine whether areas more exposed to Chinese import competition experienced larger increases in hate crimes. My analysis uses commuting zones as geographic units, following established literature that shows these areas effectively capture local economic conditions (Tolbert & Sizer, 1996).

The data used in this study comprises FBI Hate Crime Statistics, product-level import data from the U.N. Comtrade database, and local employment statistics. The identification strategy relies on variation in import competition across commuting zones, using a shift-share instrument that combines Chinese import growth with the initial employment mix in each zone. Inferring a causal relationship by using such a shift-share design is subject to two main criticisms. First, areas with a higher manufacturing employment share will be assumed to have a higher import exposure. But, as discussed in Goldsmith-Pinkham et al. (2020), higher manufacturing share might be correlated with some omitted variables affecting hate crimes. By adding area fixed effects to the regressions to control for time-invariant factors, I address this omitted variable bias. Second, import competition might be demand-driven rather than supply-driven. In other words, the rise of Chinese imports into the US might be because of increased demand in the US market rather than the increased supply capacity of China. To address this concern, I have used the import values from China in eight high-income countries as an instrument for the values of imports into the US. I found a significant positive correlation between the Chinese imports into the US and into other high-income countries, which indicates that the increased imports into the US are mostly due to the increased supply of Chinese products. Therefore, adding the area fixed effect and instrumenting the import values help isolate the exogenous impact of import competition on hate crimes, allowing for a causal interpretation of the results. Then I used the shift-share instrument in the empirical analysis of a difference-in-differences (DID) regression.

My findings reveal that higher import competition from China is linked to the significant growth of hate crimes following Trump's election, particularly in predominantly White communities. Areas with a high proportion of White citizens experienced a growth in racially motivated hate crimes while areas with a greater ethnic mix experienced more non-racially motivated hate crimes, suggesting that the drivers of hateful behavior might vary in different racial contexts. This effect became most pronounced once Trump won the election in 2016, rather than after he declared his candidacy, won the first primaries, or became the nominee for the Republican Party, which aligns with the findings of Edwards & Rushin (2018). This raises important questions about the broader mechanisms driving these shifts.

I tested several economic, social, and political factors as mechanisms that could explain the observed patterns. First, I examined the role of the unemployment rate, which can be a major driver of hate crimes (Anderson et al., 2020; Gale et al., 2002; Medoff, 1999). Second, I investigated the role of political factors, in particular, the growth in the share of Republican votes, which may reflect broader support for nationalist and anti-immigrant sentiments (Autor et al., 2020; Basu, 2021; Feigenbaum & Hall, 2015; Lyons, 2008). Finally, I considered social factors, specifically online racism scores, which capture the prevalence of hate speech and extremist ideologies in local communities (Chae et al., 2018; Green et al., 1998; Mosse, 1995). I found that, in White areas, social factors such as online racism scores are primary drivers, while in non-White areas, economic factors like unemployment play a more important role. These findings suggest that the interplay between economic distress and political rhetoric may have validated hateful behaviors, particularly in communities already predisposed to nationalist ideologies.

This study contributes to three strands of literature. First, it is the only paper to explicitly link import competition, hate crimes, and the Trump presidency. Second, it extends our understanding of hate crime drivers and their variations in different racial contexts. Third, it adds to research on globalization's social and political consequences by documenting its effects on intergroup hostility.

The remainder of the paper is organized as follows. Section 2 outlines the data sources. Section **Error! Reference source not found.** presents the descriptive evidence. Section 4 presents the empirical analysis and explores the underlying mechanisms. Section 5 summarizes the key findings and gives suggestions for future research.

2. DATA

Before presenting the data and the empirical strategy, it is necessary to identify the unit of time and local economies. As will be discussed in detail in subsequent sections, hate crime data has seasonality and follows a usual pattern throughout the year. This is why the unit of time in this study is a quarter-year. Local economies are defined by commuting zones (CZs), following Tolbert & Sizer (1996). These zones are defined as clusters of counties with strong commuting ties, and there are 741 such zones in the US. In this study, I have focused on the 722 CZs that are in the mainland US. All the data is aggregated to the CZ-quarter.

For the main data, I used FBI statistics on hate crimes, which are available from 1991 onwards. This data defines crimes motivated by the offender's bias towards a victim's race or ethnicity, religion, sexual orientation, disability, gender, or gender identity as hate crimes. For example, a crime will be classified as a hate crime if an offender destroys someone's property because of the victim's race or religion. This data source gathers information from different reporting agencies such as city, county, college and university, state, tribal, and federal agencies (*Hate Crime Statistics*, 2022). Each hate crime is reported at the incident level with details such as the originating agency identifier (ORI), time of the incident, ethnicity of the offender(s), prejudice behind the crime, number of offenders, number of victims, type of crime, etc. The ORI is a nine-character code. Thus, I used two crosswalks to match each ORI to the incident location (city) and then to the CZ level. For the first crosswalk, I used the National Archives of Criminal Justice data to link each ORI to city codes. For the second, I used Autor & Dorn's (2013) crosswalk to link each city code to the corresponding CZ code.

The data shows that hate crimes tend to have seasonality (Edwards & Rushin, 2018; Jacob et al., 2007). As seen in Figure 2-1, the number of hate crimes reliably increases in the second and third quarters of the year and drops slightly in the fourth and the first quarter. Between 1991 and 2020, there was only one instance where the number of hate crimes did not drop in the fourth quarter; namely, the last quarter of 2016, the quarter Trump was first elected as the president of the United States. From that year onwards, the overall number of hate incidents steadily rose (Figure 2-2), suggesting that the 2016 election might have caused this change in the cyclical trend. In this paper, I have assumed the Trump effect started in the last quarter of 2016 and compared the hate crime trends before and after his election.

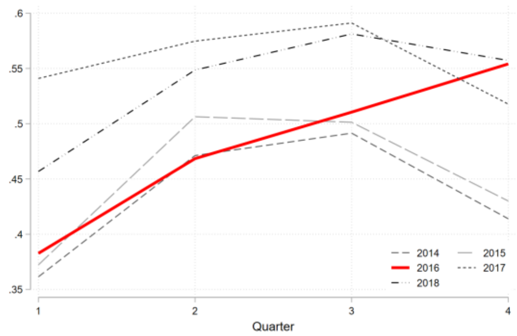


Figure 2-1. The cyclical trend of hate crimes

This figure shows the seasonality of hate crimes. The x-axis represents the quarter of the year, and the y-axis represents the number of hate crimes per 100,000 population. Each line represents one single year. Hate crimes drop in the first and last quarter of the year, except 2016, which is the only year when hate crime rates did not drop in the last quarter. The data is extracted from the FBI Hate Crime Statistics.

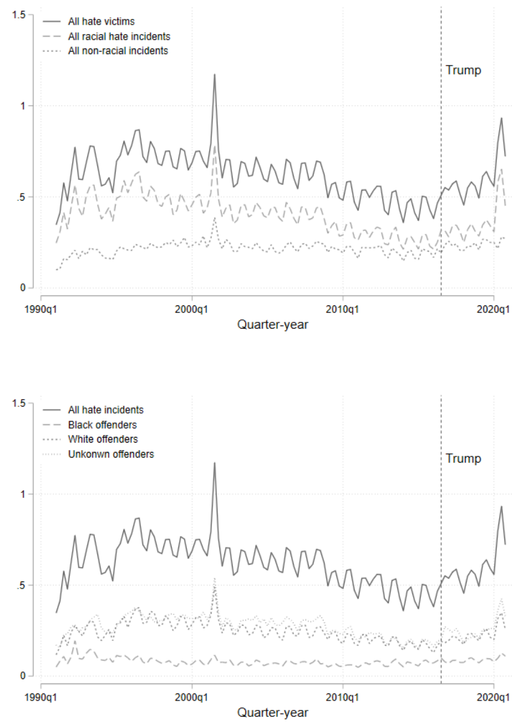


Figure 2-2. Quarterly hate crimes over the years

These figures show the time trend of hate crimes for different victims and offenders. The x-axis represents the years, and the y-axis represents the number of hate crimes per 100,000 population. The vertical line indicates the third quarter of 2016, just before Trump came to power. Racial hate crimes include hate crimes targeted at the victims because of their race (such as Asian, Hispanic, African American, or White). Non-racial hate crimes are hate crimes targeted at victims because of their non-racial characteristics, such as their religion, sexual orientation, gender identity, disability, or gender. Offenders are categorized based on their race, and if the offender is unknown, they are classified as unknown offenders. The data is extracted from the FBI Hate Crime Statistics.

A summary of hate crimes is provided in Table 2-1, in which I have calculated hate crimes per 100,000 population. Before Trump (from 2015q1 to 2016q3), the average number of hate crimes was 0.451 incidents per 100,000 population at each CZ-quarter. This value increased to

0.552 incidents after Trump's election (2016q4 to 2017q4). This increase in the number of hate crimes was driven by White or unknown offenders (cases in which the offender is not known). Since in the data, White and unknown offenders have parallel trends, I followed Green et al. (1998) and grouped these two types of offenders. I have further categorized all victims into racial and non-racial types. Table 2-2 provides summary statistics of hate crime decomposition by victim type, where both racial and non-racial hate crimes grew.

Table 2-1. Summary of hate crimes committed by offender types

	All offenders	Black offenders	Unknown offenders	White offenders
Before Trump	0.451	0.078	0.183	0.167
After Trump	0.552	0.079	0.251	0.200

This table represents the average number of hate crimes per 100,000 population for different offenders in different periods. Offenders are classified based on their race. If the offender is unknown, they are classified as unknown offenders. Before Trump is the period from 2015q1 to 2016q3, whereas after Trump is 2016q4 to 2017q4. The data is extracted from the FBI Hate Crime Statistics.

Table 2-2. Summary of hate crimes by victim type

	All hate incidents	Racially motivated	Non-racially motivated
Before Trump	0.451	0.258	0.193
After Trump	0.552	0.318	0.234

This table represents the average number of hate crimes per 100,000 population for different victims in different periods. Racial hate crimes include hate crimes targeted at victims because of their race (such as Asian, Hispanic, African American, or White). Non-racial hate crimes are hate crimes targeted at victims because of their non-racial characteristics, such as religion, sexual orientation, gender identity, disability, or gender. Before Trump is the period from 2015q1 to 2016q3, whereas after Trump is 2016q4 to 2017q4. The data is extracted from the FBI Hate Crime Statistics.

The areas that experienced the highest levels of hate crimes during Trump's presidency were New York City, Los Angeles, Boston, and Seattle. However, these cities are large metropolitan areas with a diverse population mix and had already been experiencing high rates of hate crimes before Trump's election campaign or import competition began. Despite lower overall rates of hate crimes, the Midwest and Southeast showed the largest growth of hate crime rates. These areas were the areas most impacted by Chinese import competition as well. I calculated the average number of hate crimes per 100,000 population both before and after Trump's election. After subtracting the two values, the following areas had the largest increases in hate crime rates: Norton County, Kansas; Bracken County, Kentucky; and Massac County, Illinois. Figure

2-3 depicts the areas with positive growth in hate crime before and after Trump's election, which shows Midwestern and Southeastern areas demonstrate positive growth.

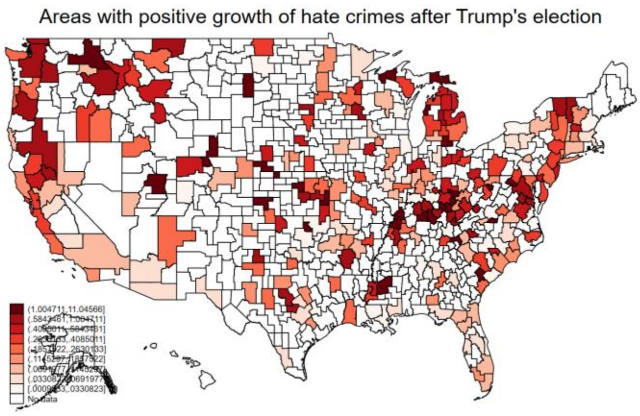


Figure 2-3. Places with positive growth in hate crimes after Trump's election

This figure shows the places with positive growth in hate crimes after Trump's election, starting from the last quarter of 2016 (average of hate incidents over 100,000 population after Trump - average of hate incidents over 100,000 population before Trump). Hate crimes in each area are calculated by the number of hate crimes in the area per 100,000 population. Before Trump is the period from 2015q1 to 2016q3, whereas after Trump is 2016q4 to 2017q4. The data is extracted from the FBI Hate Crime Statistics.

Import data was extracted from the U.N. Comtrade and Research and Expertise on the World Economy website (Gaulier & Zignago, 2010). The data was cleaned and converted from HS 6-digit codes to SIC 4-digit codes, and the values were deflated to 2012 dollars. As seen in Figure 2-4, the value of Chinese imports has drastically increased since 2001. Before 2001, China had to undergo an annual review to trade with the US; however, in 2001, China was granted permanent normal trade relations and joined the World Trade Organization (WTO) (Faux, 2000), removing all trade barriers. As a result, the US economy has faced increased competition from China. In this study, I have focused on import competition from 1999 to 2012, following Lu et al. (2018).

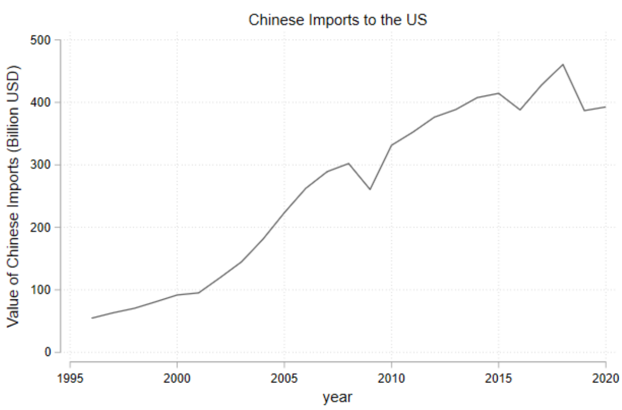


Figure 2-4. Value of Chinese imports into the US

This figure shows the trend of total value of Chinese imports in billion dollars into the US. Import data was extracted from the U.N. Comtrade and Research and Expertise on the World Economy website. The data was converted from HS 6-digit to SIC 4-digit codes. All values are deflated to 2012-dollar values.

My goal is to understand how increased import competition might affect hate crimes. To proxy for the shock to the local economy, I used the predicted imports for each CZ, based on a Bartik (shift-share) instrument. I allocated nationwide industry-specific imports to CZs based on their initial industry composition before China joined the WTO (1999), following Lu et al. (2018) and Topalova & Khandelwal (2011). The import growth per worker (IPW) in each CZ is represented by:

$$\Delta IPW_i^{China\to US} = \sum_j \frac{L_{ij}}{L_i} \frac{(M_{j2012}^{China\to US} - M_{j1999}^{China\to US})}{L_j}, \tag{1}$$

where i represents the CZ, and j represents the manufacturing industry. The import growth (shift) is the growth in import value from China to the US, which is measured from 1999 to 2012 and is deflated to the 2012 dollar value ($M_{j2012}^{China\to US} - M_{j1999}^{China\to US}$). The import growth is normalized by the initial employment in industry j (L_j is employment in industry j in 1999). The share of import competition faced by industry j in CZ i is the ratio of the employment in the industry over the total employment of the CZ ($\frac{L_{ij}}{L_i}$).

The previous specification is subject to two main criticisms. First, areas with a higher initial manufacturing share will get a higher value. But as suggested by Goldsmith-Pinkham et al. (2020), an initially higher manufacturing share might be correlated with some omitted variables that might affect hate crimes. I have controlled for CZ fixed effects in the regressions to account for any time-invariant CZ-specific characteristics. Second, this shift-share design is also subject to endogeneity since the increased imports from China might be demand-driven rather than supply-driven. Or in other words, the rise of Chinese imports into the US occurred because of increased demand in the US market rather than the increased supply of Chinese products due to the reduction of trade barriers. Therefore, I needed an instrument which is affected by increased supply of Chinese products but not increased demand of the US market. I followed Autor et al. (2013) by using the level of Chinese imports to eight other high-income countries as an instrument for the level of Chinese imports into the US.

$$\Delta IPW_i^{China\to Other} = \sum_j \frac{L_{ij}}{L_i} \frac{(M_{j2012}^{China\to Other} - M_{j1999}^{China\to Other})}{L_j}. \tag{2}$$

The specification in this equation is the same as the specification in Equation (1) except for the import values ($M_{j2012}^{China\rightarrow Other} - M_{j1999}^{China\rightarrow Other}$). In Equation (2), I have used the values of imports to eight other high-income countries instead of the import value into the US. These other countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. The critical assumption made by this instrument is that the US demand for Chinese products is uncorrelated with that of other high-income countries. Since we are using the aggregate of the imports to the eight other rich countries, it is unlikely that US demand will be correlated with that of all eight (Brandt et al., 2012).

Table 2-3 presents the summary statistics of IPW as specified in Equation (1). The average import competition from China to the US was $2,650 per worker. The values corresponding to this shift-share design are depicted on a map in Figure 2-5. As this figure shows, the Midwest and Southeast areas faced the highest import competition. Table 7-1 in the Appendices also presents the CZs with the highest IPW which are mostly located in the Midwest and Southeast. The summary statistics for the instrumented IPW as specified in Equation (2) are presented in Table 7-2 in the Appendices.

Table 2-3. Summary statistics for import competition

	N	Mean	Median	S.D.	Min	Max
Import competition$_{1999-2012}$	722	2.65	1.96	2.91	-0.21	39.87

This table shows the summary statistics of Chinese import competition faced by CZs in the US from 1999 to 2012. The import competition is calculated using a shift-share design as described by Equation (1). All values are in thousand USD and are deflated to 2012-dollar values.

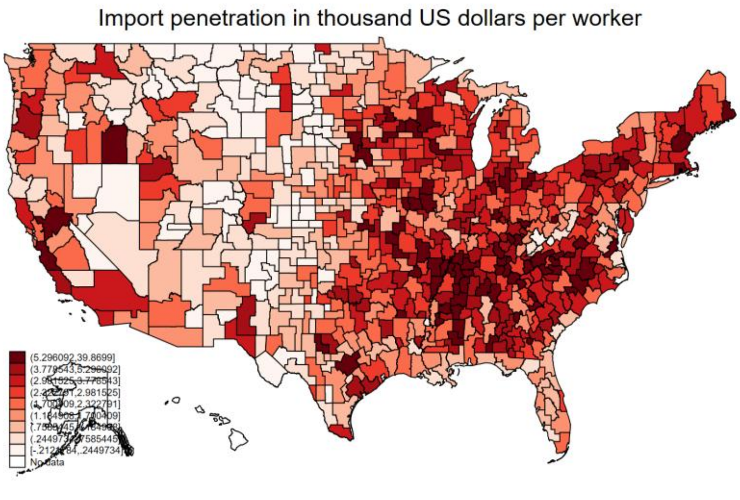


Figure 2-5. Import competition from 1999 to 2012

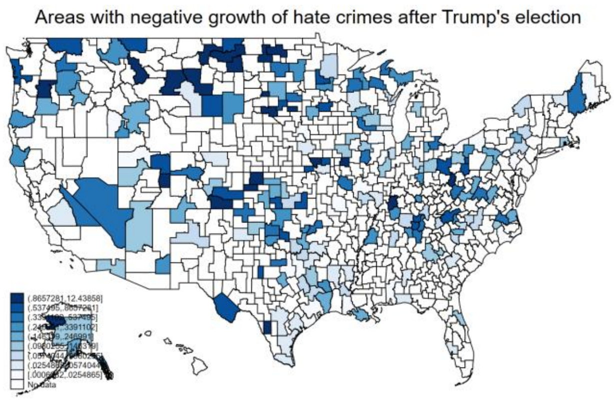
This figure shows the average import competition each CZ faced from China throughout 1999 to 2012. The import competition is measured using a shift-share design as described by Equation (1). All values are in thousand USD and are deflated to 2012-dollar values.

In the mechanism section of this paper, I have used three different variables for testing the channels leading to increased hate crimes in response to Trump's election and import competition: unemployment rate, representing economic variables; election results, representing political variables; and an online racism score, representing social variables. The data on unemployment is extracted from statistics published by the US Bureau of Labor (*US Bureau of Labor Statistics*, 2022), the election results are extracted from the MIT Election Data and Science Lab website (Lab, 2021), the data on online racism scores is downloaded from Google Trends (*Google Trends*, 2022).

And finally, the data on manufacturing employment that is used to calculate the shift-share design is extracted from the County Business Patterns (CBS). CBS is an annual dataset that provides information on employment and payroll by county and industry. The population data is extracted from US Census data and is used as a control in the proposed regressions (U.S. Census Bureau, 2022). All the data is aggregated at the CZ level using the previously specified crosswalks.

3. Descriptive Evidence

In this section, I present a graphical representation of hate crime growth and import competition using maps and event studies. The three maps in Figure 3-1 illustrate the comparison between import competition and the hate crime growth rate. The top map shows the places with negative growth in their hate crime rates, while the bottom map shows those with positive growth. The middle map shows the places with positive growth in import competition as measured by Equation (1). According to the maps, the Midwest, which is more exposed to import competition, seems to show positive growth in hate crimes. In the next step, I will evaluate any existing pre-trends of hate crimes in these areas using event studies.



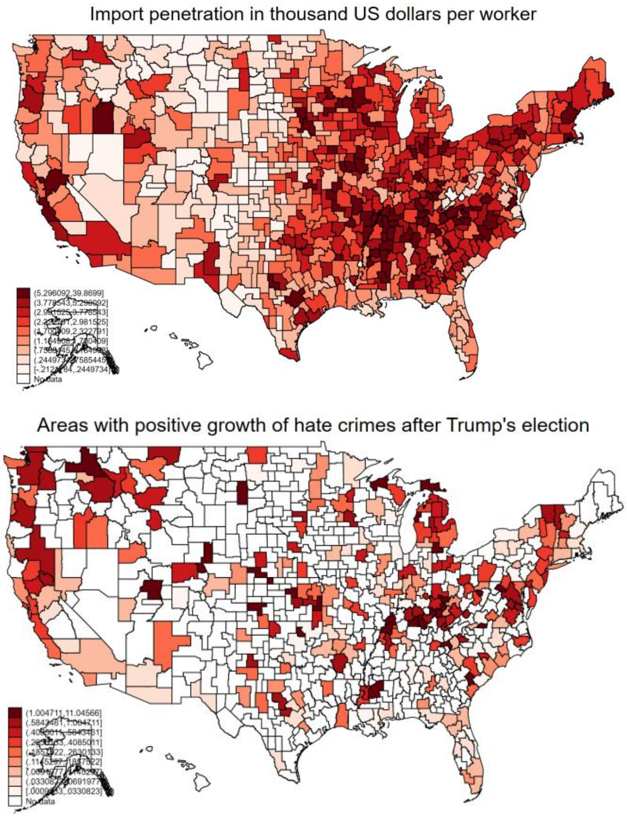


Figure 3-1. Comparison of hate crime growth and import competition

Top map: this figure shows the places with negative growth in hate crimes after Trump's election, starting from the last quarter of 2016 (average of hate incidents over 100,000 population after Trump - average of hate incidents over 100,000 population before Trump). Hate crimes in each area are calculated by the number of hate crimes in the area per 100,000 population. Before Trump is the period from 2015q1 to 2016q3, whereas after Trump is 2016q4 to 2017q4. The data is extracted from the FBI Hate Crime Statistics.

Middle map: this figure shows the average import competition each CZ faced from China throughout 1999 to 2012. The import competition is measured using a shift-share design as described by Equation (1). All values are in thousand USD and are deflated to 2012-dollar values.

Bottom map: this figure shows the places with positive growth in hate crimes after Trump's election, starting from the last quarter of 2016 (average of hate incidents over 100,000 population after Trump - average of hate incidents over 100,000 population before Trump). Hate crimes in each area are calculated by the number of hate crimes in the area per 100,000 population. Before Trump is the period from 2015q1 to 2016q3, whereas after Trump is 2016q4 to 2017q4. The data is extracted from the FBI Hate Crime Statistics.

The following equation is an event study in which I examine the trends of hate crimes in the study period.

$$y_{iq} = \sum_{k=2015Q1}^{2017Q4} b_k \times \Delta IPW_i \times 1(q = k) + CZ_i + Q_q + \varepsilon_{iq}, \tag{3}$$

where i stands for CZs and q stands for quarter-years spanning from the beginning of 2015 to the end of 2017. b_ks denote the coefficients for a set of time dummies $1(q = k)$ spanning the quarters 2015q1 to 2017q4. The base quarter is set at 2016q3, one quarter before Trump won the election. ΔIPW_i is the import competition from China to each CZ of the US, which is constructed using the shift-share design of Equation (1) and instrumented by import competition from China to eight other rich countries, as in Equation (2). The dependent variable, y_{iq}, is the number of hate crimes per 100,000 population at each CZ in each quarter-year. This event study controls for CZs and quarter-year fixed effects and ε_{iq} is the error term which is clustered at CZ level.

The purpose of the event study in Equation (3) is to examine the trends of hate crimes in response to the import competition before and after Trump's election. In Figure 3-2, I have plotted the estimated coefficient (b_k) by this equation. According to this figure, hate crimes did not exhibit an increasing trend before the election, but once Trump was elected, they started to rise. The IV estimates of this figure also have a larger standard error than the OLS estimates. This might be because of omitted variable bias or measurement errors in the import penetration estimates (both of which can cause downward bias in the OLS estimation). In addition, the IV measures the local average treatment, whereas the OLS estimates the average treatment effect (Card, 2001) which might lead to larger standard errors.

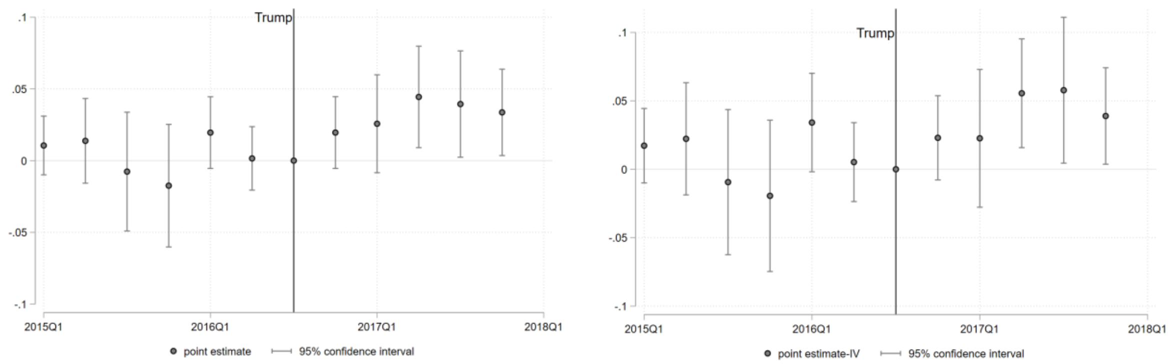


Figure 3-2. Event study using hate crimes per 100,000 population

These figures show the time trends of hate crimes with respect to Trump's election and import competition from China from 2015 to 2017. They are created by plotting the coefficient of Equation (3). The dependent variable is the number of hate crimes per 100,000 population. The import competition from China is created by a shift-share design, as given in Equation (1) using Chinese imports into the US from 1999 to 2012 (used in OLS estimates on the left). This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2) (used in IV estimates on the right). The base quarter is set to the third quarter of 2016, just before Trump took office. The hate crime data is extracted from the FBI Hate Crime Statistics. CZ fixed effect and quarter-year fixed effect are used. Errors are clustered at CZ level.

4. Empirical Analysis

After noticing no existing pre-trends in the event studies, I further analyzed the data with a difference in difference (DID) regression. The following DID regression estimates the effect of Trump and import competition on hate crimes using the FBI hate crime data:

$$y_{iq} = b \times \Delta IPW_i \times Trump_{\mathrm{q}} + \theta \mathrm{Z}_{\mathrm{iq}} + CZ_i + Q_q + \varepsilon_{iq}, \tag{4}$$

where i stands for CZs and q stands for quarter-years spanning from the beginning of 2015 to the end of 2017. The dependent variable, y_{iq}, is the number of hate crimes per 100,000 population at each CZ in each quarter-year. ΔIPW_i is the local import competition from China, which is constructed using the shift-share design of Equation (1) and instrumented by import competition from China to eight other rich countries. $Trump_{\mathrm{q}}$ is a dummy indicating Trump's presidency starting from 2016q4. This regression controls for CZs and quarter-year fixed effects, as well as one-year lagged unemployment and the log of the CZ population. ε_{iq} is the error term which is clustered at CZ level. b_1 is the coefficient of interest, which measures the response of areas more exposed to import competition to less exposed areas after Trump's election. A positive value of b_1 indicates that Trump's election led to comparatively more hate crimes in areas that had more import competition.
The main independent variable is the number of hate crimes per 100,000 population, which measures how common hate crimes might be in an area. However, the population of a CZ might change because of migration. Therefore, I have used another dependent variable for robustness checks: the number of hate crimes in each CZ-quarter over the population of the CZ in 2015. By fixing the population in 2015, I can avoid any effects of migration on the results. The robustness checks are presented in the Appendices.

4.1 First-Stage Regressions

I first have to establish a positive correlation between the two shift-share instruments that I have designed in Equation (1) and Equation (2). In these two equations, I have instrumented the Chinese imports into the US with Chinese imports into eight other countries. The results in Table 4-1 show these two values to be positively correlated, and the first stage F-statistics is found to be 293 (column (4)). This value is significant at 1%, which means the IV instrument is a strong instrument. This IV instrument is also exactly identified.

Table 4-1. The first-stage regressions

	Import competition in the US	Trump period=1 # Import competition in the US		
	(1)	(2)	(3)	(4)
Import competition $(IV)_{2012-1999}$	1.077***			
	(0.0154)			
Trump period=1 # Import competition $(IV)_{2012-1999}$		1.077***	1.076***	1.080***
		(0.0797)	(0.0810)	(0.0828)
Model	OLS	OLS	OLS	OLS
CZ FE		Y		Y
Quarter-year FE		Y	Y	Y
Controls			Y	Y
Sample	All Cross-section	All Panel	All Panel	All Panel
Observations	722	8664	8664	8664
R-squared	0.872	0.950	0.914	0.950
F stat	4897.2	182.7	226.8	293.1

This table represents the first-stage regression estimating the correlation between import competition in the US from China and its instrument. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The controls are the log of population and the lag of the unemployment rate. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

4.2 Main Findings

Table 4-2 presents the results of the DID regression (Equation (4)). In the first column, I have only regressed the number of hate crimes on the Trump dummy to see if the rise in hate crimes after Trump's election (as seen in Figure 2-1 and Figure 2-2) is numerically significant. In fact, Trump had a large positive effect on the number of hate crimes, but the results become more significant in column (2) after interacting the Trump dummy with import competition. The coefficient remains positive and significant after adding different fixed effects and controls (throughout columns (2) to (5)). The positive coefficient means that areas with higher ex-anti import competition from China witnessed a higher number of hate crimes after Trump won the 2016 election. The robustness check results are also in the same line, as presented in **Error! Reference source not found.** in the Appendices.

Table 4-2. DID estimates of Trump and import competition on hate crimes

Dependent variable: number of hate crimes per 100,000 population

	(1)	(2)	(3)	(4)	(5)
Trump period =1	0.0540*				
	(0.0301)				
Trump period=1 # Import competition from 1999 to 2012		0.0296**	0.0253**	0.0324**	0.0274**
		(0.0118)	(0.0110)	(0.0130)	(0.0125)
Model	OLS	OLS	OLS	IV	IV
CZ FE		Y	Y	Y	Y
Quarter-year FE		Y	Y	Y	Y
Controls			Y		Y
Sample	All	All	All	All	All
Observations	8664	8664	8664	8664	8664
R-squared	0.206	0.209	0.210	0.002	0.003

This table estimates the effect of Trump's election and import competition from China on hate crimes, as formalized by Equation (4). The dependent variable is the number of hate incidents per 100,000 population. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

The economic interpretation of the results is as follows. According to Table 2-3, one standard deviation more import competition is $2,905. Using the coefficient in the last column of Table 4-2, we can calculate that the effect of one standard deviation of import competition is correlated with 0.08 more hate crimes per 100,000 population per CZ-quarter. The average number of the outcome variable before Trump's presidency was 0.32. Therefore, one standard deviation more import competition is associated with a 24.9% growth in hate crimes.

4.3 Heterogeneity Analysis

I speculate that since Trump was promoting White supremacy and bashing China and migrants for the poor economy (Gabbatt, 2020; Wu, 2018), the effect of import competition on White areas and non-White areas might be different. Also, the literature shows that white and non-White offenders might have different motivations for committing hate crimes. Green et al. (1998) and Troesken & Walsh (2019) suggest that White identity is an important factor in incentivizing White offenders to discriminate against people of color. Therefore, they have classified hate crimes committed by White or unknown offenders differently than those by other offenders. Aside from the literature, the FBI data also shows that the majority (79%) of hate crimes are committed by White and unknown offenders.

To investigate this hypothesis, I divided CZs into majority White and majority non-White (hereafter referred to as White and non-White areas) based on the median proportion of Whites in 2012. CZs whose numbers of White residents were above the median were denoted as White areas, and the remainder as non-White. Table 7-4 provides brief statistics of White areas and non-White areas. White areas are usually less populated and, on average, have a 90% White population.

The effects of Trump and import competition are almost twice as large for White areas as for non-White. This means that after the 2016 election, hate crimes in the White areas that had more exposure to Chinese imports increased more than in non-White areas. This suggests the sensitivity of the White population to Trump's rhetoric (Edwards & Rushin, 2018; Hinojosa Ojeda & Telles, 2021; Hodwitz & Massingale, 2021; Reja, 2021). It can also suggest that White identity motivation behind some hate crimes (Reardon et al., 2015; Troesken & Walsh, 2019). I checked the same regression using the population in 2015 (to rule out any migration between CZs) and found a similar effect (Table 7-5).

Table 4-3. DID estimates for White and non-White areas.

Dependent variable: number of hate crimes per 100,000 population						
	(1)	(2)	(3)	(4)	(5)	(6)
Trump period=1 # Import competition from 1999 to 2012	0.0424**	0.0368		0.0123*	0.0162*	
	(0.0210)	(0.0225)		(0.00703)	(0.00891)	
Trump period=1 # Import competition (IV)			0.0349			0.0203**
			(0.0216)			(0.00995)
Model	OLS	IV	Reduced form	OLS	IV	Reduced form
CZ FE	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Sample	White areas	White areas	White areas	Non-White areas	Non-White areas	Non-White areas
Observations	4332	4332	4332	4332	4332	4332
R-squared	0.181	0.003	0.180	0.341	0.007	0.341

This table estimates the effect of Trump's election and import competition from China on hate crimes in CZs with predominantly White populations and areas with predominantly non-White populations. CZs are classified as White areas if the White share of the population is above the median. The dependent variable is the number of hate incidents per 100,000 population. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Based on the FBI data, between 2015 and 2017, 57% of hate crimes were racially motivated. Thus, I have decomposed hate crimes into racial and non-racial hate crimes and used them in a DID regression as in Equation (4) to see if they are differently affected by import competition and Trump's presidency. The results of these regressions in Table 4-4 show that, in White areas, import competition induces racially motivated hate crimes, while in non-White areas, it induces non-racial hate crimes. The former finding aligns with earlier studies highlighting the role of White identity in motivating hate crimes committed by Whites (Green et al., 1998; Troesken & Walsh, 2019). The latter finding (the lack of a significant effect of import competition in non-White areas on racial hate crimes) can be explained by the demographic characteristics shown in Table 7-4. Non-White areas are likely to be large metropolitan areas with a diverse population mix. This diversity may act as a deterrent against racially motivated hate crimes, as potential offenders are regularly exposed to different racial groups. Consequently, hate incidents may be more likely to target other minority characteristics such as religion, sexual orientation, or gender identity (as the results in column (9) show, the coefficient on non-racial hate crimes in non-White areas in significant). To investigate the potential association of import competition with different categories of non-racial hate crimes, I decomposed such crimes and analyzed them, as shown in Table 7-7 in the Appendices. These crimes include hate crimes against people of different religions, sexual orientations, disabilities, genders, and gender identities. None of the results show a significant coefficient, showing that none of these groups were specifically targeted in response to Trump and import competition.

Table 4-4. DID estimates for racial and non-racial hate crimes

Dependent variable: number of hate crimes per 100,000 population	All	Racial	Non-racial	All	Racial	Non-racial	All	Racial	Non-racial
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trump period=1 # Import competition from 1999 to 2012	0.0274**	0.0182**	0.00927	0.0368	0.0310*	0.00586	0.0162*	0.00472	0.0115*
	(0.0125)	(0.00867)	(0.00574)	(0.0225)	(0.0160)	(0.00953)	(0.00891)	(0.00479)	(0.00666)
Model	IV	IV	IV	IV	IV	IV	IV	IV	IV
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sample	All	All	All	White areas	White areas	White areas	Non-White areas	Non-White areas	Non-White areas
Observations	8664	8664	8664	4332	4332	4332	4332	4332	4332
R-squared	0.003	0.003	0.001	0.003	0.004	0.001	0.007	0.008	0.002

This table estimates the effect of Trump's election and import competition from China on racial and non-racial hate crimes in areas with a predominantly White population and areas with a predominantly non-White population. Racial hate crimes include hate crimes targeted at the victims because of their race (such as Asian, Hispanic, African American, or White). Non-racial hate crimes are hate crimes targeted at victims because of their non-racial characteristics, such as religion, sexual orientation, gender identity, disability, or gender. The dependent variable is the number of hate incidents per 100,000 population. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

4.4 Potential Mechanisms

As described in the Introduction, import competition can have economic, political, and social consequences, and the same categories of factors are associated with hate crimes. Economic factors, such as unemployment and competition in the labor market, market wage rate, and income gap can incentivize hate crimes (Anderson et al., 2020; Gale et al., 2002; Medoff, 1999; Pinderhughes, 1993). Political factors, such as the presence of far-right parties, are also associated with an increase in such crimes (Cochrane & Nevitte, 2014; Edwards & Rushin, 2018; Falk et al., 2011; Koopmans, 1996). And last but not least, social factors, such as nationalism and racism, are another root of hate crimes (Basu, 2021; Lyons, 2008). For this reason, I chose three variables to test three potential mechanisms leading to the rise in hate crimes in response to Trump and import competition. These three variables are changes in the unemployment rate, the growth of vote share for Republicans, and an online racism score (their summary statistics are provided in Table 7-8) respectively representing the economic loss, political shifts, and social background of CZs. In the subsequent paragraphs, the relationship between these factors and import competition, as well as their relationship with hate crimes, will be tested.

First, to examine the role of economic conditions in the rise of hate crimes, I focus on the changes in the unemployment rate, a key indicator of economic distress. The data on unemployment is extracted from the US Bureau of Labor Statistics (2022) and has been aggregated at the CZ level to capture labor market dynamics.

To quantify economic losses, I subtracted the unemployment rate in 2012 from the unemployment rate in 1999:

$$
\begin{aligned}
&\mathit{Changes\ In\ Unemployment}\ \mathrm{Rate}_{(1999-2012)} \\
&\qquad = \mathit{Unemployment}_{2012} - \mathit{Unemployment}_{1999}\ .
\end{aligned}
$$

A positive value in this calculation indicates an increase in unemployment, reflecting economic deterioration, while a negative value suggests a decline in the unemployment rate, implying economic improvement. By tracking these changes over time, I assess whether regions that experience greater economic decline also report higher incidents of hate crimes.

Second, I tested the association of hate crimes with voting behavior through changes in the voting share of Republicans from 2000 to 2012. The election results are extracted from the MIT Election Data and Science Lab website (Lab, 2021) and are aggregated at the CZ level. I measured the changes in the Republican vote share by subtracting the republican vote share in the 2012 presidential election from the republican vote share in the 2000 presidential election. A positive value implies an increased support for the Republican party, while a negative value implies the opposite. As before, I assessed whether regions that experience greater support for Republicans also report higher growth of hate incidents.

$$RepublicanGain_{2012-2000} = RepublicanVoteShare_{2012} - RepublicanVoteShare_{2000}$$

To establish a positive correlation between import competition and positive vote gain for Republicans, I performed a simple DID regression. I regressed the above variable ($RepublicanGain_{2012-2000}$) on the import competition measure in Equation (1). The results are given in Table 7-9 and are similar to those of Autor et al. (2020) suggesting that import competition is correlated with the growth of vote share for the Republican party in areas with a predominantly White population.

Finally, I tested the association of social factors with hate crimes, focusing on racism as a measure of social unrest. The data on online racism scores is downloaded from Google Trends and has been normalized (*Google Trends*, 2022). Following Anderson et al. (2020) and Chae et al. (2015, 2018), I used Google Trends scores for searches of the "N-word" as a proxy for area-level racism. Google Trends search data has been used by many authors studying social phenomena. To name a few, Anderson et al. (2020) used Google Trends data to measure the relationship of the Great Recession on anti-black racial animosity, and Kearney & Levine (2015) used it to explain the reduction in teen births due to increased interest in contraceptive use and abortion.

Google Trends works in the following way: it calculates the proportion of searches containing a given term to all searches within a given time and geographic area, offering insights into the relative popularity of search queries over time and across different regions. Google can identify the geography of each user through the IP address. Based on this information, Google Trends assigns an index value of 100 for the place with the highest proportion of searches containing the specified term. Then the rest of the areas are assigned an indexed value based on the proportion of searches compared to the area with the highest proportion. In other words, the area where the relative search is half of the maximum value will get an index value of 50. This data is downloadable at the state, designated market area (DMA), and city level.

In this study, I obtained the Google searches of the “N-word” for every DMA, since a DMA is the closest match to a CZ. DMAs are geographic regions that group counties based on television viewing areas, which I mapped to CZs using a crosswalk methodology. These searches were only available from 2008 onwards; therefore, I used the values of 2012 as a proxy for online racism for this analysis. Since the values are between 0 and 100, I normalized them as follows: I subtracted the mean value of the sample from each observation and divided it by the standard deviation. Then, to examine any relationship between online racism and import competition, I ran a simple regression, where I regress local import competition on the racism score. The results are presented in Table 7-10. They show a significant positive correlation between import competition and racism score in the areas with a majority White population.

To identify the potential mechanisms behind the observed results, I used mediative analysis (Baron & Kenny, 1986). I interacted each of the proposed variables with import competition and added it to the main DID regression (Equation (4)). Any variable that demonstrated significant explanatory power in the regressions would be considered a potential channel leading to the growth of hate crimes. The results of mediative analysis are presented in Table 4-5. They show that the growth in the unemployment rate and racism are two potential mechanisms playing significant roles in the rise of hate crimes, while the growth republican vote share has no significant effect. However, the previous results show that the derivational forces behind the rise of hate crimes might differ between White and non-White areas. Therefore, I conducted separate analyses for the potential mechanisms for these two types of areas.

Table 4-5. DID estimates for determinants of hate crimes

Dependent variable: number of hate crimes per 100,000 population							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trump period=1 # Import competition from 1999 to 2012	0.0253**	0.0274**		0.0234*	0.0262**	0.0222*	0.0193*
	(0.0110)	(0.0125)		(0.0123)	(0.0126)	(0.0114)	(0.0116)
Trump period=1 # Import competition (IV)			0.0296**				
			(0.0130)				
Trump period=1 # Change in the rate of unemployment from 2000 to 2012				2.401**			2.056**
				(0.996)			(0.998)
Trump period=1 # Republican vote share gain from 2000 to 2012					0.330		0.0822
					(0.450)		(0.434)
Trump period=1 # Normalized racism score in 2012						0.0584*	0.0502
						(0.0337)	(0.0328)

Model	OLS	IV	Reduced form	IV	IV	IV	IV
CZ FE	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y
Sample	All	All	All	All	All	All	All
Observations	8664	8664	8664	8664	8664	8604	8604
R-squared	0.210	0.003	0.210	0.003	0.003	0.004	0.004

This table investigates the potential channels affecting the rise in hate crimes in response to the election of Trump and import competition from China. The dependent variable is the number of hate incidents per 100,000 population. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 4-6 shows the meditative analysis for the White areas. Among the three variables, racism score is the only factor that is significantly correlated with import competition, while changes in unemployment rate and republican vote share do not play important roles. This means that in White areas, import-induced hate crimes are mainly driven by social factors such as racism. The robustness check presented in Table 7-12 shows similar results.

Table 4-6. DID estimates for determinants of hate crimes in White areas

Dependent variable: number of hate crimes per 100,000 population

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trump period=1 # Import competition from 1999 to 2012	0.0424**	0.0368		0.0306	0.0326	0.0163	0.0138
	(0.0210)	(0.0225)		(0.0217)	(0.0231)	(0.0218)	(0.0219)
Trump period=1 # Import competition (IV)			0.0349				
			(0.0216)				
Trump period=1 # Change in rate of unemployment from 2000 to 2012				2.911			1.633
				(2.110)			(2.000)
Trump period=1 # Republican vote share gain from 2000 to 2012					0.784		-0.333
					(0.809)		(0.730)
Trump period=1 # Normalized racism score in 2012						0.188**	0.196**
						(0.0921)	(0.0898)
Model	OLS	IV	Reduced form	IV	IV	IV	IV
CZ FE	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y
Sample	White areas	White areas	White areas	White areas	White areas	White areas	White areas
Observations	4332	4332	4332	4332	4332	4272	4272
R-squared	0.181	0.003	0.180	0.003	0.003	0.005	0.005

This table investigates the potential channels affecting the rise in hate crimes in response to the election of Trump and import competition from China in predominantly White CZs. The dependent variable is the number of hate incidents per 100,000 population. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 4-7 shows the results for the non-White areas in which the growth of the unemployment rate can explain the rise in hate crimes, while the republican vote share gain and online racism seem to have little effect. This suggests that in non-White areas, the economic factors are the channels leading to increased hate crimes. These results are confirmed by the robustness checks given in Table 7-13 in the Appendices.

Table 4-7. DID estimates for determinants of hate crimes in non-White areas

Dependent variable: number of hate crimes per 100,000 population

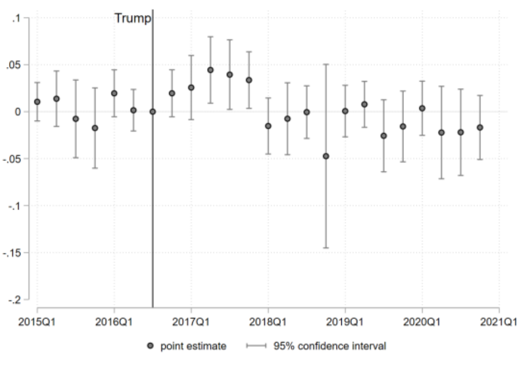
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trump period=1 # Import competition from 1999 to 2012	0.0123*	0.0162*		0.0128	0.0167*	0.0144*	0.0118
	(0.00703)	(0.00891)		(0.00823)	(0.00904)	(0.00840)	(0.00792)
Trump period=1 # Import competition (IV)			0.0203**				
			(0.00995)				
Trump period=1 # Change in rate of unemployment from 2000 to 2012				2.427**			2.384**
				(1.014)			(0.988)
Trump period=1 # Republican vote share gain from 2000 to 2012					-0.311		-0.456
					(0.327)		(0.350)
Trump period=1 # Normalized racism score in 2012						0.0190	0.0186
						(0.0208)	(0.0219)
Model	OLS	IV	Reduced form	IV	IV	IV	IV
CZ FE	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y
Sample	Non-White areas	Non-White areas	Non-White areas	Non-White areas	Non-White areas	Non-White areas	Non-White areas
Observations	4332	4332	4332	4332	4332	4332	4332
R-squared	0.341	0.007	0.341	0.009	0.007	0.007	0.010

This table investigates the potential channels affecting the rise in hate crimes in response to the election of Trump and import competition from China in predominantly non-White areas. The dependent variable is the number of hate incidents per 100,000 population. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

A comparison of Table 4-6 and Table 4-7 show that the coefficients for White areas are usually larger but less significant. This might be because White areas are usually smaller cities with large White population shares, meaning any hate crime incidents add more fluctuations to the data. For this reason, I performed the same regression as in Table 4-6 but weighted it based on the population of the CZ. In this regression, the effect of each CZ will be proportionate to its population; therefore, the areas with smaller populations will have a smaller effect on the coefficients. The results are presented in Table 7-14. The coefficients of this weighted regression are smaller than those of the non-weighted one (Table 4-6). This means that cities with smaller populations play an important role in the growth of the hate crime rate in White areas. This suggests that people in less populated cities that are more exposed to import competition from China became more likely to commit hate crimes after Trump took office.

4.5 Long-run Event Study

The focal period of this study was a relatively short frame of time from early 2015 to late 2017. I tried expanding this analysis to longer periods, for example, from early 2015 to late 2020, but the results faded away as we got further from 2016. Figure 4-1 depicts the interaction coefficient of Trump and import competition in the event study in Equation (3). It is apparent that this coefficient increases in the few quarters following Trump's election but then falls. This leaves us with the question of why Trump's election induced hate crimes in the more import-exposed areas in the early stages of his presidency but not later on. It is possible that the rise in hate crimes was initiated in the more import-exposed CZs, but later on spread into neighboring areas. However, answering this question is beyond the scope of this research, and I leave it for future work.



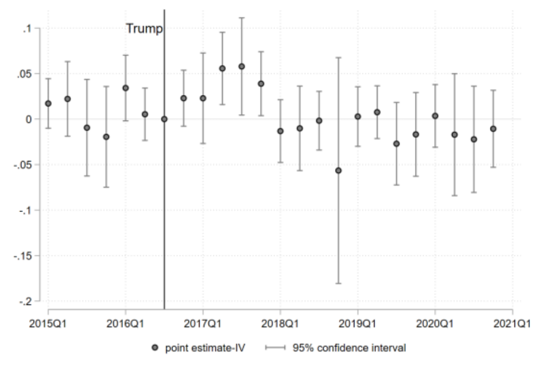


Figure 4-1. Long-run event study using hate crimes per 100,000 population

These graphs show the time trends of hate crimes with respect to the election of Trump and import competition from China from 2015 to 2020. They are created by plotting the coefficient of Equation (3). The dependent variable is the number of hate crimes per 100,000 population. The graph on the left is created using an OLS model, while that on the right is created using an IV model. The base quarter is set to the third quarter of 2016, just before Trump took office. The hate crime data is extracted from the FBI Hate Crime Statistics The import competition from China is created by a shift-share design, as given in Equation (1) using Chinese imports into the US from 1999 to 2012 (used in OLS estimates on the left). This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2) (used in IV estimates on the right). CZ fixed effect and quarter-year fixed effect are used. Errors are clustered at CZ level.

4.6 Discussion

This study reveals distinct patterns in the relationship between import competition and hate crimes during 2015–2017. During this time, different demographic areas exhibited different patterns and motivations for hate incidents. In White-majority areas, which usually have a small homogeneous White population, the growth in hate crime rates was twice as large as in non-White areas, and the hate crimes were largely motivated by race, spurred by higher import competition and Trump's presidency. These findings align with Green et al. (1998) who argued that White communities may employ hate crimes as a deterrent mechanism against demographic change. The FBI data supports this interpretation, showing that 79% of hate offenders are White or unknown.

The underlying mechanism behind hate crimes in White areas appears to be primarily social in nature. The literature can explain this mechanism. One stream of literature establishes that import competition in the US has negative socio-economic consequences. For example, populations that were more exposed to import competition experienced negative sentiment towards minorities (Autor et al., 2020; McManus & Schaur, 2016). Another stream of the literature establishes that the interaction between economic stress and social identity can cause intergroup hostility (Jackson, 1993). Therefore, the economic pressure of import competition coupled with Trump's nationalist rhetoric may have intensified existing racial tensions and provoked hostility towards those of other races in White areas.

In non-White areas, which are typically large metropolitan areas with an approximately 60% White population, the mechanisms are more complex. Whilst import competition with the added effect of Trump's election led to more hate crimes in these areas, the mechanism appears to be economic, with the unemployment rate playing a significant mediating role. This finding reconciles with the results of the previous literature on the economic motivations behind hate crimes (Anderson et al., 2020; Gale et al., 2002; Green et al., 1998; Medoff, 1999). However, it is a surprising finding that import competition and Trump led to a growth in non-racially, as opposed to racially, motivated hate crimes in these areas. I hypothesize that the diverse racial composition of these areas might have created a buffering effect, redirecting hate crimes towards other social minorities.

The timing of increased hate crimes, coinciding with Trump's election, requires careful attention. It raises the question at which stages of the political journey do xenophobic leaders influence societal behavior: when they announce their candidacy, gain significant public support, secure the nomination of a major political party, or assume public office? To answer this question, I aggregated the FBI data to a monthly level and identified the key milestones in Trump's political trajectory: announcing his candidacy, winning his first set of primaries, accepting the official nomination of the Republican Party, and winning the election. Figure 7-1 presents these milestones and illustrates that among them, winning the election had the largest impact on hate crimes, suggesting that taking office served as a crucial turning point in emboldening expression of xenophobic attitudes. This pattern aligns with criminological theories that emphasize the transmission of social behaviors and norms within communities (Cohen, 1995). Exposure to inflammatory and xenophobic rhetoric can reinforce and legitimize prejudiced attitudes, creating a social climate where hate crimes become more frequent. Trump's election—and the rhetoric surrounding it—likely intensified this transmission effect, shifting social norms and making the public expression of xenophobic ideologies more acceptable (Bursztyn et al., 2020; Edwards & Rushin, 2018). This normalization is reflected in numerous reported hate incidents, where offenders referred to Trump while committing hate crimes (Kyle Scott Clauss, 2016; Lindsey Bever, 2017).

This study addresses a significant gap in the economic literature regarding the relationship between import competition and hate crimes. While DiLorenzo (2021) found a significant effect between trade-related layoffs and hate crimes, my results suggest that the relationship becomes significant under a specific political environment and within specific demographic compositions.

This research contributes to our understanding of how economic shocks interact with political and social factors influence intergroup tensions while highlighting the importance of demographic context in analyzing hate crimes.

5. CONCLUSION AND RECOMMENDATIONS

This study investigates the association between hate crimes and import competition (from China) under Trump's presidency in different demographic contexts. I found that places with a higher level of import competition experienced relatively more hate crimes after the 2016 election. I further found that the magnitude of this effect and the motivating factors behind it are different in predominantly White and predominantly non-White areas.

The combined effect of import competition and Trump's election on hate crimes is larger in White areas than in non-White areas. In White areas, hate crimes are mostly racially motivated and driven by social factors such as racism, whereas in non-White areas, they are generally non-racial and likely to be motivated by economic factors such as the unemployment rate. The former finding aligns with studies such as Green et al. (1998) and Jackson (1993). As White areas are usually less populated and more homogeneously White, import competition coupled with Trump's rhetoric might have strengthened the sense of White identity in these areas, resulting in more racial hate crimes. While the latter finding is aligned with Anderson et al. (2020) and Medoff (1999) where competition over scarce economic resources can lead to a rise in hate crimes.

This study, like others, is subject to limitations. First, the main source of hate crime data used in this study is the FBI statistics. However, it is well accepted that hate crimes are underreported (Carrega & Krishnakumar, 2021; Choi, 2021; Stening, 2021), the results observed in this study might not fully represent the real rate of hate crimes. To address this limitation, future studies could use more inclusive data, such as online measures of hate speech, instead of the number of reported hate crimes. Second, the proxies for economic, political, and social factors used in this study—namely unemployment rate, Republican vote share, and online racism scores—are crude and could be substituted with more sophisticated proxies in future studies. Thirdly, the observed results are short-lived. Therefore, future studies could address the long-term impact of import competition on hate crimes.

In recent years, a rich literature has formed on the potential consequences of import competition (especially Chinese import competition) and globalization. Although globalization and trade have long-term gains, they are also associated with short-term losses. This study adds to the literature by suggesting that import competition coupled with other social factors can increase hate crimes, at least for a short period. This consequence has never been thoroughly investigated by economists or sociologists. Thus, this study makes an important contribution to the literature and can help policymakers to better understand hate crimes and protect potential victims.

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7. APPENDICES

7.1 Tables

Table 7-1. CZs with the highest import competition from China

CZ Name	CZ Code	$\Delta IPW_i^{China \to US}$ (thousand dollars)
Sioux City, IA-NE	28001	39.87
Hutchinson-Redwood Falls, MN	21201	21.34
Raleigh-Durham-Chapel Hill, NC	01701	19.77
San Jose, CA	37500	17.11
Asheville, NC	01204	14.21
Meridian, MS	10400	13.81
Decatur-Huntsville, AL	6000	13.06
Kirksville-Moberly-Marshall, MO-Centerville, IA	26101	12.86
Sioux Falls, SD	26503	11.64
Jackson, TN	04903	11.30

This figure shows the CZs that faced the highest import competition from China over the period 1999 to 2012. The import competition is measured using a shift-share design as described by Equation (1). All values are in thousand USD and are deflated to 2012-dollar values.

Table 7-2. Summary statistics for the instrumented import competition

	N	Mean	Median	S.D.	Min	Max
Import competition $(IV)_{1999\text{-}2012}$	722	2.74	2.18	2.52	-0.17	22.34

This table shows the summary statistics of Chinese import competition faced by CZs in the US over the period 1999 to 2012. The import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. All values are in thousand USD and are deflated to 2012-dollar values.

Table 7-3 DID estimates of Trump and import competition on hate crimes

Dependent variable: number of hate crimes per 100,000 population in 2015

	(1)	(2)	(3)	(4)	(5)
Trump period =1	0.0553*				
	(0.0300)				
Trump period=1 # Import competition from 1999 to 2012		0.0298**	0.0254**	0.0325**	0.0275**
		(0.0118)	(0.0110)	(0.0130)	(0.0125)
Model	OLS	OLS	OLS	IV	IV
CZ FE		Y	Y	Y	Y

Quarter-year FE		Y	Y	Y	Y
Controls			Y		Y
Sample	All	All	All	All	All
Observations	8664	8664	8664	8664	8664
R-squared	0.211	0.212	0.002	0.003	0.211

This table estimates the effect of Trump's election and import competition from China on hate crimes, as formalized by Equation (4). The dependent variable is the number of hate incidents per 100,000 population for 2015. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 7-4. Statistics for White population share in 2012

	N	Average population	Average White population share	Min of the White population share	Max of the White population share
White CZs	361	155,670	90.7%	82.02%	98.6%
Non-White CZs	361	707,868	61.5%	3%	81.9%

This table shows the White share of the population in different CZs. The population in 2012 has been used to classify a CZ as predominantly White or non-White. Areas where the White share of the population is above the median are classified as White CZs, whereas those where it is below the median are classified as non-White CZs. Population data was extracted from the US Census.

Table 7-5. DID estimates for White and non-White CZs

Dependent variable: number of hate crimes per 100,000 population in 2015

	(1)	(2)	(3)	(4)	(5)	(6)
Trump period=1 # Import competition	0.0426**	0.0371		0.0124*	0.0162*	
	(0.0210)	(0.0225)		(0.00703)	(0.00885)	
Trump period=1 # Import competition (IV)			0.0352			0.0203**
			(0.0215)			(0.00989)
Model	OLS	IV	Reduced form	OLS	IV	Reduced form
CZ FE	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Sample	White areas	White areas	White areas	Non-White areas	Non-White areas	Non-White areas
Observations	4332	4332	4332	4332	4332	4332
R-squared	0.183	0.003	0.182	0.343	0.007	0.344

This table estimates the effect of Trump's election and import competition from China on hate crimes in CZs with predominantly White populations and areas with predominantly non-White populations. CZs are classified as White areas if the White share of the population is above the median. The dependent variable is the number of hate incidents per 100,000 population in 2015. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from

2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 7-6. DID estimates for racial and non-racial hate crimes

Dependent variable: number of hate crimes per 100,000 population in 2015	All	Racial	Non-racial	All	Racial	Non-racial	All	Racial	Non-racial
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trump period=1 # Import competition from 1999 to 2012	0.0275**	0.0182**	0.00927	0.0371	0.0311*	0.00598	0.0162*	0.00476	0.0114*
	(0.0125)	(0.00866)	(0.00571)	(0.0225)	(0.0160)	(0.00949)	(0.00885)	(0.00480)	(0.00659)
Model	IV	IV	IV	IV	IV	IV	IV	IV	IV
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sample	All	All	All	White areas	White areas	White areas	Non-White areas	Non-White areas	Non-White areas
Observations	8664	8664	8664	4332	4332	4332	4332	4332	4332
R-squared	0.003	0.003	0.001	0.003	0.004	0.001	0.007	0.008	0.002

This table estimates the effect of Trump's election and import competition from China on racial and non-racial hate crimes in White and non-White areas. Racial hate crimes include hate crimes targeted at victims because of their race (such as Asian, Hispanic, African American, or White). Non-racial hate crimes are those targeted at victims because of non-racial characteristics, such as religion, sexual orientation, gender identity, disability, or gender. The dependent variable is the number of hate incidents per 100,000 population in 2015. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 7-7. Decomposition of non-racial hate crimes in non-White commuting zones

Dependent variable: number of hate crimes per 100,000 population	all hate	race hate	Non-race hate	religion hate	sexual orientation hate	disability hate	gender hate	gender identity hate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trump period=1 # Import competition from 1999 to 2012	0.0162*	0.00472	0.0115*	0.00112	0.00319	0.00443	0.00217	0.000212
	(0.00891)	(0.00479)	(0.00666)	(0.00291)	(0.00222)	(0.00278)	(0.00340)	(0.000189)
Model	IV	IV	IV	IV	IV	IV	IV	IV
CZ FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Sample	Non-White areas	Non-White areas	Non-White areas	Non-White areas	Non-White areas	Non-White areas	Non-White areas	Non-White areas
Observations	4332	4332	4332	4332	4332	4332	4332	4332
R-squared	0.007	0.008	0.002	0.001	0.001	0.001	0.004	0.001

This table estimates the effect of Trump's election and import competition from China on non-racial hate crimes in non-White CZs. Non-racial hate crimes are hate crimes targeted at victims because of their non-racial characteristics, such as their religion, sexual orientation, gender identity, disability, or gender. The dependent variable is the number of hate incidents per 100,000 population. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 7-8. Summary statistics for the mechanism variables.

	N	Mean	Standard Deviation	Min	Max
$UnemploymentChange_{2012-1999}$	722	0.02626	0.0227	-0.094	0.084
$RepublicanGain_{2012-2000}$	722	0.01600	0.0653	-0.174	0.326
Racism $score_{2012}$	717	-0.00003	1.0006	-1.870	4.089

This table shows the summary statistics of the variables used to investigate the potential mechanisms. All values are at CZ level. The data on unemployment was extracted from the US Bureau of Labor Statistics, the election results were extracted from the MIT Election Data and Science Lab website, and the data on online racism scores was downloaded from Google Trends and has been normalized.

Table 7-9. Import competition and Republican vote share growth

Dependent variable: republican vote share gain from 2000 to 2012

	(1)	(2)	(3)
Import competition from 1999 to 2012	0.00233**	0.00471***	0.000362
	(0.00107)	(0.00143)	(0.000925)
Model	OLS	OLS	OLS
Sample	All	White areas	Non-White areas
Observations	722	361	361
R-squared	0.011	0.034	0.000

This table estimates the correlation between Republican vote share gain from 2000 to 2012 with import competition from China between 1999 to 2012. Both variables are computed at the CZ level. The analysis is done separately for White areas and non-White areas. The election results were extracted from the MIT Election Data and Science Lab website. The import competition is calculated by Equation (1). Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 7-10. Regression of racism on import competition

Dependent variable: normalized racism score in 2012

	(1)	(2)	(3)
Import competition from 1999 to 2012	0.0721***	0.103***	0.0579
	(0.0273)	(0.0233)	(0.0425)
Model	OLS	OLS	OLS
Sample	All	White areas	Non-White areas
Observations	717	356	361
R-squared	0.044	0.106	0.030

This table estimates the correlation between the online racism score in 2012 with import competition from China between 1999 to 2012. Both variables are computed at the CZ level. The analysis is done separately for White areas and non-White areas. The racism score has been calculated by the share of racist words to all Google searches and was extracted from Google Trends. The import competition is calculated by Equation (1). Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 7-11. DID estimates on determinants of hate crimes

Dependent variable: number of hate crimes per 100,000 population in 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trump period=1 # Import competition from 1999 to 2012	0.0254**	0.0275**		0.0234*	0.0263**	0.0224**	0.0194*
	(0.0110)	(0.0125)		(0.0122)	(0.0126)	(0.0114)	(0.0115)
Trump period=1 # Import competition (IV)			0.0297**				
			(0.0130)				
Trump period=1 # Change in unemployment rate from 1999 to 2012				2.400**			2.059**
				(0.992)			(0.994)
Trump period=1 # Change in Republican vote share from 2000 to 2012					0.310		0.0629
					(0.446)		(0.430)
Trump period=1 # racism score 2012						0.0579*	0.0500
						(0.0337)	(0.0329)
Model	OLS	IV	Reduced form	IV	IV	IV	IV
CZ FE	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y
Sample	All	All	All	All	All	All	All
Observations	8664	8664	8664	8664	8664	8604	8604
R-squared	0.212	0.003	0.212	0.004	0.003	0.004	0.004

Note: This table investigates the potential channels affecting the rise in hate crimes in response to Trump's election and import competition from China. The dependent variable is the number of hate incidents per 100,000 population in 2015. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 7-12. DID estimates for determinants of hate crimes in White CZs

Dependent variable: number of hate crimes per 100,000 population in 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trump period=1 # Import competition from 1999 to 2012	0.0426**	0.0371		0.0308	0.0330	0.0166	0.0141
	(0.0210)	(0.0225)		(0.0217)	(0.0230)	(0.0217)	(0.0217)
Trump period=1 # Import competition (IV)			0.0352				
			(0.0215)				
Trump period=1 # Change in unemployment rate from 1999 to 2012				2.912			1.629
				(2.103)			(1.994)
Trump period=1 # Change in Republican vote share from 2000 to 2012					0.754		-0.370
					(0.802)		(0.726)
Trump period=1 # racism score 2012						0.187**	0.197**
						(0.0920)	(0.0900)
Model	OLS	IV	Reduced form	IV	IV	IV	IV
CZ FE	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y
Sample	White areas	White areas	White areas	White areas	White areas	White areas	White areas
Observations	4332	4332	4332	4332	4332	4272	4272
R-squared	0.183	0.003	0.182	0.003	0.003	0.006	0.006

This table investigates the potential channels affecting the rise in hate crimes in response to Trump's election and import competition from China in White CZs. The dependent variable is the number of hate incidents per 100,000 population in 2015. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 7-13. DID estimates for determinants of hate crimes in non-White CZs

Dependent variable: number of hate crimes per 100,000 population in 2015							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trump period=1 # Import competition from 1999 to 2012	0.0124*	0.0162*		0.0128	0.0167*	0.0144*	0.0118
	(0.00703)	(0.00885)		(0.00818)	(0.00899)	(0.00839)	(0.00790)
Trump period=1 # Import competition (IV)			0.0203**				
			(0.00989)				
Trump period=1 # Change in unemployment rate from 1999 to 2012				2.426**			2.391**
				(1.011)			(0.984)
Trump period=1 # Change in Republican vote share from 2000 to 2012					-0.319		-0.458
					(0.326)		(0.348)
Trump period=1 # racism score 2012						0.0179	0.0175
						(0.0209)	(0.0219)
Model	OLS	IV	Reduced form	IV	IV	IV	IV
CZ FE	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y
Sample	Non-White areas	Non-White areas	Non-White areas	Non-White areas	Non-White areas	Non-White areas	Non-White areas
Observations	4332	4332	4332	4332	4332	4332	4332
R-squared	0.343	0.007	0.344	0.009	0.007	0.007	0.010

This table investigates the potential channels affecting the rise in hate crimes in response to Trump's election and import competition from China in non-White CZs. The dependent variable is the number of hate incidents per 100,000 population in 2015. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

Table 7-14. Weighted DID estimates

Dependent variable: number of hate crimes per 100,000 population

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trump period=1 # Import competition from 1999 to 2012	0.0155	0.00950		0.00686	0.00998	0.00486	0.00472
	(0.0130)	(0.0147)		(0.0147)	(0.0147)	(0.0151)	(0.0150)
Trump period=1 # Import competition (IV)			0.00974				
			(0.0151)				
Trump period=1 # Change in unemployment rate from 1999 to 2012				2.470			1.523
				(2.072)			(2.260)
Trump period=1 # Change in Republican vote share from 2000 to 2012					-0.113		-0.520
					(0.498)		(0.553)
Trump period=1 # racism score 2012						0.0801	0.0951*
						(0.0534)	(0.0572)
Model	OLS	IV	Reduced form	IV	IV	IV	IV
CZ FE	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y
Sample	White areas	White areas	White areas	White areas	White areas	White areas	White areas
Observations	4332	4332	4332	4332	4332	4272	4272
R-squared	0.364	0.002	0.364	0.003	0.002	0.004	0.005

Note: This table investigates the potential channels affecting the rise in hate crimes in response to Trump's election and import competition from China in White CZs. The regressions are weighted by the CZ's population. The dependent variable is the number of hate incidents per 100,000 population. The time frame is from 2015q1 to 2017q4, and the Trump period is assumed to start from 2016q4. The import competition from China is created by a shift-share design, as given in Equation (1), using Chinese imports into the US from 1999 to 2012. This import competition is instrumented by Chinese imports into eight high-income countries, as given in Equation (2). The controls are the log total population and lag unemployment. CZ and quarter-year fixed effects are used. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level. Standard errors are clustered at the CZ level.

7.2 Figures

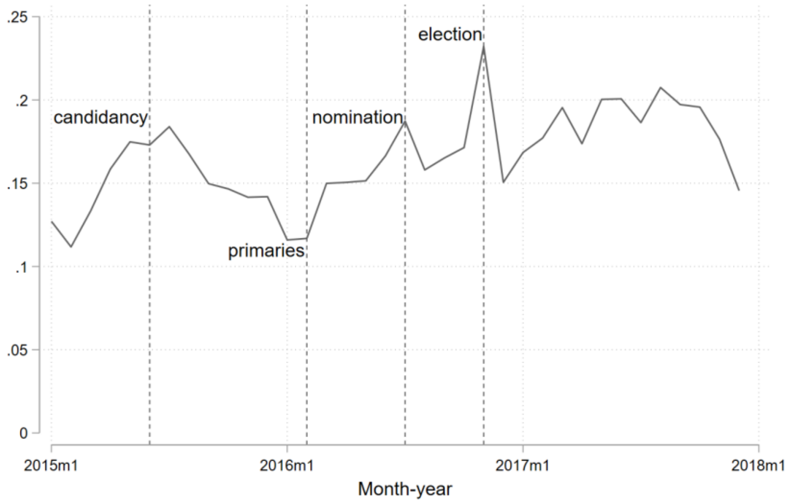

Figure 7-1. The most important dates leading to Trump's election

This figure shows the time trend of hate crimes with the most important dates leading up to Trump's election. The x-axis represents the months, and the y-axis represents the number of hate crimes per 100,000 population. The vertical lines are: candidacy declaration in June 2015, winning the first primaries in February 2016, party nomination in July 2016, and winning the election in November 2016. The data is extracted from the FBI Hate Crime Statistics.