Information Shocks, Attitudes toward Immigrants, and Hate Crime

Jake Bradley ⓡ * Facundo Albornoz ⓡ † Silvia Sonderegger ⓡ ‡
Jesús Rodríguez ⓡ § Devesh Rustagi ¶‖

Abstract

We study how national political shocks that reveal xenophobic sentiment affect hate crime. We develop a social-norms model in which individuals care about matching both local and national behavior, but only observe local attitudes toward immigrants. Electoral outcomes that unexpectedly signal strong national anti-immigrant sentiment therefore generate larger "belief shocks" in locally tolerant areas, encouraging xenophobic individuals there to express hostility more openly. We test the model using data on racially and religiously motivated hate crimes in all 304 Community Safety Partnerships in England and Wales from 2002–2019, combined with pre-event attitudes and beliefs from the British Election Study. Difference-in-differences estimates show that a one–standard-deviation higher pre-event pro-immigrant attitude is associated with a 0.11 standard-deviation increase in hate crime after the UK Independence Party's 2014 European election victory and a 0.16 standard-deviation increase after the 2016 Brexit referendum. Belief-shock measures and survey evidence on the expression of anti-immigrant views support the proposed mechanism.

JEL: D70, D80, Z13

Keywords: Information shock, xenophobia; attitudes, beliefs, hate crime United Kingdom

*University of Nottingham and IZA; email: `jake.bradley@nottingham.ac.uk`
†University of Nottingham, CONICET and CEPR; email: `Facundo.Albornoz@nottingham.ac.uk`
‡University of Nottingham; email: `Silvia.Sonderegger@nottingham.ac.uk`
§University of Nottingham; email: `jesus.rodriguez@nottingham.ac.uk`
¶University of Warwick; email: `devesh.rustagi@warwick.ac.uk`
‖We thank Roland Bénabou for his valuable insights on a previous version of this paper. We are also grateful to Fabrizio Adriani, Gilat Levy, Daniel Seidmann, Francesco Squintani, and specially Leonardo Bursztyn, Antonio Cabrales, Giacomo Corneo, Guillermo Cruces and Carlo Schwarz, for valuable comments and suggestions, as well as seminar respondents at the Freie Universität Berlin, King's College London, University of Birmingham, University of Bristol, University of East Anglia, University of Loughborough, University of Nottingham, University of Pennsylvania, Royal Economic Society 2019, NICEP 2018 and University of Warwick. Justus Meyer, Nada Abdelghany, and Maria Sampaolesi provided outstanding research assistance.

I. Introduction

There is a growing concern over rise in populism and hate crimes against immigrants and minorities associated with it (Guriev and Papaioannou, 2022). Understanding the mechanisms through which populism causes a surge in hate crime is crucial to develop appropriate policy responses. One possibility is that areas with historically persistent xenophobia are more likely to experience surges in hate crime (Voigtländer and Voth, 2012), in part due to persuasion from listening to radio (Adena et al., 2015) and coordination facilitated by social media (Bursztyn et al., 2019). Another possibility is through information shocks from political events that reveal previously unknown tolerance for xenophobia in the population of interest, thereby challenging pluralistic ignorance (Lohmann, 1994; Kuran, 1991). Such events can trigger rapid changes in social norms such that xenophobic behaviors that were previously considered unacceptable now become more tolerable (Bursztyn, Egorov and Fiorin, 2020). A common theme across these impressive studies is that (regardless of the underlying mechanism) more xenophobic places are the ones that experience a surge in xenophobia. In this paper, we document a counterintuitive result: we show that information shocks from political events lead a higher surge in xenophobia driven hate crime not in xenophobic but in tolerant areas.

What explains this counterintuitive result? We argue that people know the distribution of anti-immigrant preferences at the local level, but not at the national level. This creates an important heterogeneity in how people react to new information about the nation as a whole. In pro-immigrant areas, people are more surprised by a revelation of strong national anti-immigrant sentiment, resulting in a larger behavioral change driven by strategic complementarity at the national level. This change is mainly driven by xenophobic people in pro-immigrant areas who switch their behavior from tolerant to intolerant after discovering the "mood of the nation" – that is, after learning that their own preferences align with the majority at the national level. In contrast, in anti-immigrant areas, people are less surprised, resulting in a smaller behavioral change. In situations where Bursztyn, Egorov and Fiorin (2020) would forecast a rise in hateful behavior, we sometimes predict no increase, and in situations where they would expect no change, we predict a rise in hate.

We first present a model that formalizes this mechanism. We then present empirical evidence in line with the model. Our study takes place in the UK, where we capitalize on two "earthquake" information revelation events: the UK Independent Party (UKIP) winning the popular vote in the 2014 European Parliament elections (27% of the vote, up from 15.6% in 2004), and the Leave victory in the 2016 Brexit referendum. Both events were widely described in the media as political shocks, revealed that anti-immigrant attitudes were more widespread than previously believed, and were followed by a large surge in hate crime.

We consider a model in which individuals seek to align their actions with their personal preferences, behavior at the local level, and, importantly, behavior at the national level. In the absence of events that reveal true national sentiment, people form beliefs about the country by extrapolating from the sentiment in their local area, which they observe more directly. Events that disclose prevailing national sentiment act as information revelation events. The effect of this information revelation on behavior depends on the size of the information shock, and we show that this shock is heterogeneous across areas.

An event that reveals widespread anti-immigrant sentiment at the national level generates a larger information shock in areas where anti-immigrant sentiment is uncommon, that is, where most people are tolerant. In these areas, xenophobes now become aware that although they are a local minority, they are part of the majority at the country level. It is the arrival of this new information that causes them to change their behavior in the post-event period from tolerant to intolerant. In contrast, in areas where xenophobes are already the majority, they experience a smaller information shock, as they already expected to be part of a national majority. This means that their behavior before and after the event is more similar, and there is no rise or only a moderate rise in hate crime in these xenophobic areas.

Our model directly addresses heterogeneous treatment effects of new information, which has been largely overlooked in the literature. It predicts a counterintuitive positive correlation between (i) local pro-immigrant sentiment and (ii) the rise of xenophobic expression following the revelation of national-level xenophobia.

Our empirical analysis uses a difference-in-differences approach to test these predictions. We exploit the two UK information shocks and study how they affect hate crime. Our study comprises all Community Safety Partnerships (CSPs) in England and Wales. To capture xenophobic behavior, we use data on racially or religiously motivated hate crime at the CSP level from the second quarter of 2002 to the fourth quarter of 2019. We measure attitudes toward immigrants just before the UKIP election and the Brexit referendum using individual-level data from the British Election Study (BES), which covers more than 30,000 individuals and allows us to construct CSP-level measures of attitudes toward immigrants.

Our theory suggests that the information shock from these events is larger for xenophobic individuals living in CSPs where they are in a minority – that is, where most people have positive attitudes toward immigrants. This implies a positive association between pre-event attitudes toward immigrants and the surge in hate crime in the aftermath of UKIP and Brexit. Consistent with this, we compare hate crimes before and after the events in CSPs with stronger and weaker pro-immigrant attitudes, controlling for CSP fixed effects (to absorb time-invariant differences across CSPs such as geographic characteristics and culture), quarter fixed effects (to absorb common shocks and seasonality), and a rich set of time-varying controls. The identifying assumption is that, absent the events, hate crimes would have evolved similarly in CSPs with stronger versus weaker pro-immigrant attitudes. We provide event-study evidence that this assumption likely holds and further introduce region- and police-force-specific time trends to address remaining concerns.

In line with our theoretical framework, we find a strong positive association between attitudes toward immigrants and the surge in hate crimes in the post-event periods, particularly after Brexit. Our estimates suggest that a one-standard-deviation increase in pre-event pro-immigrant attitudes is associated with an increase in hate crime of around 0.16 standard deviations in the post-Brexit period. This is a large effect relative to the mean. Our results are robust to controlling for population, the share of EU and non-EU immigrants in the CSP, season-specific fixed effects, and region- and police-force-specific time trends.

We conduct a series of robustness and falsification exercises. We show that our findings are not driven by changes in other types of crime (such as murder, burglary, or driving offenses), by CSPs with very large populations, by alternative survey waves used to measure attitudes, or by differential changes in economic conditions or crime reporting across areas. Moreover, we provide evidence on the mechanism by showing that belief shocks – measured using BES data on the perceived likelihood of Brexit – are larger in more pro-immigrant CSPs and are positively associated with hate crime in the post-event period.

Our paper contributes to the literature on pluralistic ignorance and social norms, where information shocks about what others privately think generate large shifts in behavior because individuals realize that others share their views (e.g. Lohmann, 1994; Kuran, 1991). We show that when information about attitudes is revealed at the national level, these mechanisms generate important and previously overlooked heterogeneity: areas that are more tolerant ex ante can experience larger post-event surges in xenophobic expression. We also contribute to the literature on xenophobic propaganda, media, and hate crime, and to work on strategic complementarities in political participation and expressive behavior, which underscores how new information interacts with prior beliefs. Our model and empirical results reveal counterintuitive patterns linking preferences, beliefs, and hate crime in the post-event period, and they are useful for identifying and targeting policy toward areas where hate crimes may surge in response to national-level information shocks.

Finally, the rest of the paper is organized as follows. Section II.A. presents the conceptual framework and derives the main theoretical predictions. Section II.B. discusses the effect of an information shock and the resulting heterogeneity across areas. Section III.B. describes the institutional context, data, and measurement. Section VI. presents the empirical strategy and main results, together with robustness checks and falsification tests. Section VI. then investigates the mechanism through beliefs and individual-level responses, and the final section concludes.

II. Conceptual framework

Background We consider a country of measure 1 containing continuum of individuals who are divided into geographical districts of equal size (for simplicity). All individuals move simultaneously. Each individual i in district d selects his *behavior* $a_i \in \mathbb{R}$ to maximize expected payoff. This depends on (i) how closely the individual's behavior matches a preference parameter $\alpha_i \in \mathbb{R}$ reflecting his intrinsic preferences, and (ii) how closely it conforms to a reference behavior $\overline{a}^{n_d}$ defined as $\overline{a}^{n_d} \equiv \lambda \overline{a} + (1-\lambda)\,\overline{a}^d$, where $\overline{a}^d$ and $\overline{a}$ represent average behavior in district d and country-wide, respectively, and $0 < \lambda \leq 1$. The reference behavior $\overline{a}^{n_d}$ is meant to capture what is considered socially acceptable – the social norm – and is shaped by behavior locally as well as country-wide, with the relative importance of the latter being parameterized by λ. Note that the motivation for conforming to $\overline{a}^{n_d}$ need not necessarily stem from a desire for *external* social approval. It can just as readily arise from an internal drive to adopt a behavior that is consistent with one's identity – as e.g. in George A Akerlof and Rachel E Kranton (2000); Roland Bénabou and Jean Tirole (2011).[1] In this interpretation, λ captures the extent to which individuals identify with the country as opposed to their local area.

Individual preferences Individual preferences are given by the sum of two components: a district-specific component P^d, and an idiosyncratic component, ε_i. The district-specific component is in turn given by the sum of a mean preference parameter μ and a random element e^d, common to all individuals in district d. We can think of e^d as capturing the effect of district-specific characteristics, while μ corresponds to mean preferences in the whole country, when specific district characteristics are averaged out. To sum up, therefore, the preference parameter α_i^d of an individual i belonging to district d is equal to

$$\alpha_i^d = \mu + e^d + \varepsilon_i \tag{1}$$

where μ, the (unobservable) mean preference in the whole country, is drawn as $N(\overline{\mu}, \Theta)$, e^d represents the district-specific shock to preferences, drawn as $N(0,1)$ with $e^{d_1} \perp e^{d_2}$, and ε_i, the idiosyncratic shock to preferences, is drawn as $N(0, \sigma)$, with $\varepsilon_i \perp \varepsilon_j$ for $i \neq j$, and $\varepsilon_i \perp e^d$ for any i and d. The variable $\overline{\mu}$ can be thought of as a common prior.

Information Each individual observes average preferences within his district, $P^d = \mu + e^d$,

[1] We follow e.g., George A Akerlof (1980); Moti Michaeli and Daniel Spiro (2017); P Grout, S Mitraille and S Sonderegger (2015) and Cristina Bicchieri, Eugen Dimant and Silvia Sonderegger (2020) in adopting a consequentialist approach, in the sense that social esteem or self-esteem follows directly from individual behavior and its relationship with the norm. Another branch of the literature, such as B Douglas Bernheim (1994); Roland Bénabou and Jean Tirole (2011) or Fabrizio Adriani and Silvia Sonderegger (2019), focuses instead on the case where behavior is not approved or stigmatized *per se*, but only to the extent to which it reveals information about an individual's underlying type.

but is unable to discriminate between μ and e^d, the country–wide component and the district–specific shock affecting his preferences. People form conjectures about μ from the information at their disposal. Consider an individual i who has observed P^d. Given the normality assumptions, his expectation of μ is as follows

$$E(\mu \mid P^d) = \frac{\Theta}{1+\Theta}P^d + \frac{1}{1+\Theta}\overline{\mu}. \tag{2}$$

Payoffs The payoff of an individual i belonging to district d is equal to

$$u_i = -\theta\left(a_i - \alpha_i\right)^2 - (1-\theta)\left(a_i - \overline{a}^{n_d}\right)^2. \tag{3}$$

where, as mentioned, $\overline{a}^{n_d} \equiv \lambda\overline{a}+(1-\lambda)\,\overline{a}^d$. The parameter $\theta \in (0,1)$ captures the concern for aligning one's behavior with one's personal preferences relative to conforming with the reference behavior.

II.A. The Equilibrium

Our equilibrium concept is Perfect Bayesian Equilibrium. Each individual i in district d chooses his behavior a_i to maximize his expectation of (3), where the expectation is taken with respect to $\overline{a}^{n_d}$. Differentiating the objective function and rearranging delivers i's best reply,

$$a_i = \theta\alpha_i + (1-\theta)\,E\left(\overline{a}^{n_d}|P^d\right). \tag{4}$$

In words, each individual's behavior is a weighted average of their own preferences and their expectations of the reference behavior. In equilibrium, all individuals choose their action according to (4) and expectations are consistent with equilibrium behavior. For analytical convenience, we consider the computationally easier case of a continuum of districts.

Proposition 1 *When μ is unobservable, the unique linear symmetric equilibrium of the game is given by,*

$$a_i = \theta\alpha_i + \gamma_0 P^d + (1-\theta-\gamma_0)\overline{\mu} \tag{5}$$

where $\gamma_0 \equiv \frac{\theta(1-\theta)(\Theta+1-\lambda)}{\theta+\lambda(1-\theta)+\theta\Theta} < 1-\theta$.

We can compare the equilibrium described in Proposition 1 with the equilibrium that obtains in an alternative scenario, in which μ is publicly observable.

Proposition 2 *When μ is publicly observable, the unique linear symmetric equilibrium of the game is given by,*

$$a_i = \theta\alpha_i + \gamma_1 P^d + (1-\theta-\gamma_1)\mu \tag{6}$$

where $\gamma_1 \equiv \frac{\theta(1-\theta)(1-\lambda)}{\theta+\lambda(1-\theta)} < 1-\theta$.

Proof: Proofs for Proposition 1 and 2 are provided in the Appendix.

Next, we explicitly characterize average behavior in the whole country and individual districts.

Corollary 1 *When μ is unobservable, average behavior is $\overline{a} = (\theta + \gamma_0)\mu + (1 - \theta - \gamma_0)\overline{\mu}$ in the whole country and $\overline{a}^d = (\theta + \gamma_0)\, P^d + (1 - \theta - \gamma_0)\overline{\mu}$ in district d.*

Corollary 2 *When μ is publicly observable, average behavior is $\overline{a} = \mu$ in the whole country and $\overline{a}^d = (\theta + \gamma_1)\, P^d + (1 - \theta - \gamma_1)\mu$ in district d.*

II.B. The effect of an information shock on behavior

Consider an event that reveals the electorate's private preferences, above and beyond previous information available.[2] The pre-event environment is one where, as in Proposition 1, true average preferences are unobserved. The post-event environment is one where, as in Proposition 2, true average preferences are observed.[3]

Consider first the country as a whole. From Corollaries 1 and 2, the change in average behavior towards immigrants before and after the information revelation event is

$$\overline{a}_{after} - \overline{a}_{before} = (1 - \theta - \gamma_0)\, (\mu - \overline{\mu})\,. \tag{7}$$

In what follows, without loss of generality we adopt the convention that higher values of a (resp., α) correspond to more anti-immigrant behavior (resp., preferences).

Corollary 3 *The necessary and sufficient condition for the event to induce behavior across the country to become more anti-immigrant on average is that $\mu - \overline{\mu} > 0$.*

For the event to increase anti-immigrant behavior, true average preferences (revealed by the event) must be more anti-immigrant than the ex-ante prior. The role of new information is crucial to appreciate the mechanism behind the change in behavior. A larger value of $\mu - \overline{\mu}$ means that the *surprise effect* of the new information is larger, and, consequently, the behavioral change is also larger.[4] Intuitively, the information revelation event generates a behavioral reaction only to the extent to which the information it reveals is unexpected.

[2] Intuitively, suppose that in a binary election or referendum, individuals obey the following voting strategy: for some constant $\widehat{\alpha}$, all those with preferences $\alpha_i \leq \widehat{\alpha}$ vote A while all those with $\alpha_i > \widehat{\alpha}$ vote B. Clearly enough, once the shares of A and B votes across the nation become public information, this perfectly reveals the true value of μ and makes it common knowledge, as in Proposition 2.

[3] In Appendix X, we show that the results extend to the case where the event simply provides *more* information about μ than was previously available, without perfectly revealing it.

[4] The difference between true mean preferences, μ, and mean pre-event beliefs about μ is $\mu - E[E(\mu \mid P^d)] = \frac{\mu - \overline{\mu}}{1+\Theta}$ and is therefore directly proportional to $\mu - \overline{\mu}$.

The next result shows that the surprise effect varies across areas.

Lemma 1 *When μ is unobservable, average beliefs about μ in district d is $E(\mu \mid P^d) = \frac{\Theta}{1+\Theta}P^d + \frac{1}{1+\Theta}\overline{\mu}$. The difference between true μ and previous average beliefs about μ in district d is therefore*

$$\mu - E_d[E(\mu \mid P^d)] = \mu - \frac{\Theta}{1+\Theta}P^d - \frac{1}{1+\Theta}\overline{\mu},$$

decreasing in P^d.

Proof: Follows straightforwardly from Bayesian updating.

Intuitively, to form beliefs about preferences across the country, people partially extrapolate from preferences in their own area.[5] People living in pro-immigrant areas tend to believe that the country as a whole is pro-immigrant and vice versa for people living in anti-immigrant areas. The surprise effect of an information shock that reveals that, at the national level, people dislike immigrants is therefore greater in areas that are pro-immigrant.

Corollary 4 *The difference in average behavior in district d before and after the information revelation event is decreasing in P^d. It is equal to*

$$\overline{a}^d_{after} - \overline{a}^d_{before} = P^d(\gamma_1 - \gamma_0) + (1-\theta-\gamma_1)\mu - (1-\theta-\gamma_0)\overline{\mu} \tag{8}$$

where $\gamma_1 - \gamma_0 = -\frac{\theta\Theta\lambda(1-\theta)}{(\theta+\lambda(1-\theta))(\theta(1-\lambda)+\lambda+\theta\Theta)} < 0.$

In words, the model predicts that areas where individuals have stronger anti-immigrant preferences experience a *smaller* change in behavior following the information revelation event.[6] Intuitively, people living in anti-immigrant areas are less surprised by the new information than people living in pro-immigrant areas. They therefore do not adjust their behavior as much.[7]

[5] This is somewhat reminiscent of the false consensus effect, a well known concept in psychology that refers to the tendency of people to overestimate the extent to which their preferences are typical of those of others. Our analysis shows that, when mean preferences are not observed, using own preferences (or preferences in one's own area, as in our model) to predict the preferences of other individuals (other areas) is perfectly consistent with Bayesian updating – see also Christoph Vanberg (2019) and Fabrizio Adriani and Silvia Sonderegger (2015) for other illustrations of this general point.

[6] We are implicitly focusing on the empirically relevant case where $\overline{a}^d_{after} - \overline{a}^d_{before} > 0$ for all d.

[7] In Appendix **??**, we investigate the alternative idea that, rather than being driven by the desire to conform to social norms, people may want to adopt a behavior that signals to those around them that their preferences are similar to theirs, and argue that this model would generate the opposite prediction to Corollary 4.

III. Field Setting and Data

III.A. Field Setting

The UK provides an ideal setting for our study because of two prominent and unexpected information shocks that exposed previously hidden anti-immigrant attitudes at the national level. We describe these below.

UKIP's Election.– The first information shock is the UK Independent Party's (UKIP) unexpected victory in the European Parliament elections held in May 2014, in which UKIP increased its vote share by more than 60 percentage points relative to the previous election, from 15.6% in 2004 to 26.6% in 2014. It was the first time since 1910 that a party other than Labour or Conservative had won the largest number of seats in any election. A leading newspaper in the UK, the Guardian, reported this as a "political earthquake."[8] UKIP was the only party that explicitly advocated for leaving the European Union and used xenophobic rhetoric, so its surprise victory signaled that anti-immigrant attitudes were more widespread among the population than previously expected.

Brexit Referendum.– The second information shock is the Brexit referendum that was held in June 2016, a vote that resulted in the UK eventually leaving the European Union (EU). The referendum outcome was described by the BBC as "a huge surprise."[9] In fact, on voting day, British bookmakers placed the likelihood of a Leave victory to be between 13% and 17% — thus vastly underestimating the outcome. The Leave campaign made explicit use of anti-immigrant rhetoric, framing immigration as a central issue in its appeal to voters. In the aftermath of Brexit, hate crimes in Britain hit record high.[10]

III.B. Data

In the UK, crime data are recorded by the 43 territorial police forces. Each police force typically oversees several Community Safety Partnership (CSP) areas within its jurisdiction. The CSPs are empowered under the Crime and Disorder Act (1998) to formulate and implement strategies to tackle local crime, disorder and antisocial behavior in their communities. Our unit of analysis is a CSP. We focus on England and Wales, as data from Scotland and Northern Ireland are not available at the CSP level.

We use several different sources to collect CSP level data on hate crime, other crimes, attitudes towards immigrants, and beliefs on the likelihood of UKIP election as well as

[8] Available at https://www.theguardian.com/politics/2014/may/26/ukip-european-elections-political-earthquake

[9] Available at https://www.bbc.com/news/uk-politics-eu-referendum-36616028

[10] Available at https://www.bbc.co.uk/news/uk-38976087.

Brexit. We supplement these analyses with a survey measuring individual level propensity to express personal views towards immigrants following the Brexit referendum. We describe the data below, except for data on beliefs and expression of personal views, which we present in section VI.

Hate Crime.– The police force in England and Wales records a criminal offense in the category of hate crime if it is perceived to be motivated by hostility or prejudice towards someone based on their race, ethnicity or religion. These crimes are defined by statute and will typically be subject, if prosecuted, to stricter sentencing than the equivalent crime, absent the racial or religious motivation. The data on hate crime are publicly available from the Office of National Statistics (ONS) at the level of a local authority. There are 315 local authorities in England and Wales, which uniquely correspond to 298 CSPs. Five local authorities have multiple CSPs in them, so we assign hate crime in these authorities to the most populous CSP. Our final sample comprises 304 CSPs. We use quarterly data on hate crime for 71 quarters spanning 18 years, from 2002 to 2019. We do not use data from 2020 onwards because of confounding with COVID pandemic.

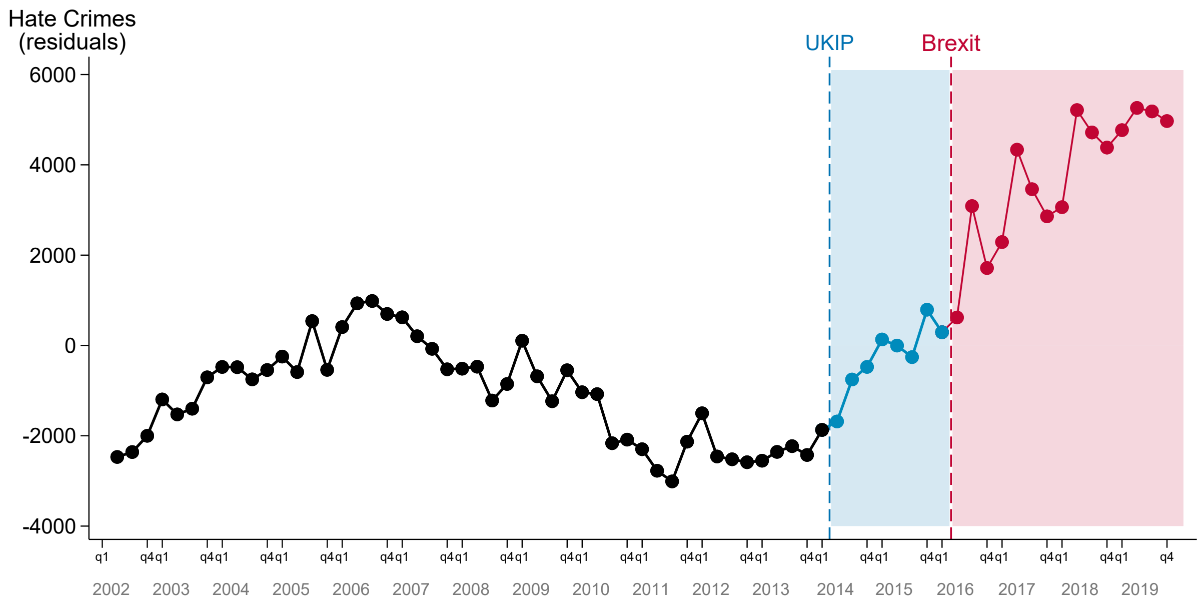


Figure 1: Evolution of Hate Crime over Time

Notes. The figure depicts the evolution of reported hate crimes. The Y-axis displays the residuals of reported hate crimes obtained from a CSP-level regression of the total number of hate crimes on season indicators to capture the seasonal variation in hate crime and an indicator variable that takes the value of 1 during Q3 and Q4 of 2005 and 0 otherwise, to account for the 7/7 London Bombing. The blue solid line corresponds to the post-UKIP period, while the red line corresponds to the post-Brexit period.

Figure 1 plots total hate crime in England and Wales over time after accounting for an indicator for 7/7 London bombing and indicators for seasons. It shows large variation. Crucially, there is a steep and steady surge in hate crime post UKIP (shaded in blue) and Brexit (shaded in pink) events. This pattern is not observed in periods prior to the events.

Panel A of Table A.1 reports summary statistics on hate crime per CSP per quarter. It ranges between 0 and 616, the average being 31.96 (s.d. 43.41). In the econometric analysis, we use standardized measure of hate crime, with mean 0 and standard deviation of 1.

Attitudes Toward Immigrants.– We collect data on attitudes toward immigrants from the British Election Study (BES), which is an individual level panel survey with approximately 30,000 respondents. We use data on attitudes from panel waves that were conducted just before the UKIP and Brexit events, respectively.

- For the UKIP event, we use data from Wave 1 of the BES, which was conducted between 20 February 2014 and 9 March 2014, two months before the EU Parliament Election.
- For the Brexit event, we focus on Wave 8 of the BES, which was conducted on 11 May 2016, slightly more than a month before the Brexit referendum.

We measure attitudes using responses to two questions: (a) "Do you think immigration is good or bad for Britain's economy?" The respondents could choose their answer on a scale of 1-7, where 1 implies "bad for the economy" and 7 implies "good for the economy"; and (b) "Do you think that immigration undermines or enriches Britain's cultural life?". The respondents could choose their answer on a scale of 1-7, where 1 implies "undermines" and 7 implies "enriches". The BES data has identifiers for local authority, which we match with CSP using the same procedure that we used for matching hate crime. Since both attitudes are measured on the same scale, we take their average at the CSP level. Our results hold when we consider each attitude separately. Broadly speaking, these attitudes can be considered as capturing important cultural traits like tolerance and respect towards immigrants Tabellini (2010). Panel A of Table A.1 shows that attitudes toward immigrants range from 2.62 to 5.71, the average being is 3.636 (s.d. 0.458). In the econometric analysis, we use standardized measure of attitudes with mean 0 and standard deviation of 1.

IV. Empirical Strategy

We examine the association between hate crime and attitudes towards immigrants in post UKIP and Brexit events using a difference-in-differences approach. We compare the evolution of hate crime in CSPs with stronger versus weaker attitudes towards immigrants before and after the UKIP / Brexit events. Specifically, we estimate the following equation for each event separately:

$$Hate_{it} = \alpha + \beta(Post\ Event_t \times Attitudes_i) + \gamma \mathbf{X}_{it} + \tau_t + \eta_i + \epsilon_{it} \tag{9}$$

where $hate_{it}$ is the standardized hate crime in CSP i in quarter t. *Event* refers to the UKIP election to the European Parliament or the Brexit referendum. Specifically, when the event is the UKIP election, we use *Post UKIP* – a binary indicator that takes a value of 1 for quarters from May 2014 onward, otherwise 0. When the event is the Brexit referendum, we use *Post Brexit* – a binary indicator that takes a value of 1 for quarters from June 2016 onward, otherwise 0. *Attitudes* is towards immigrants and is also standardized. τ is a fixed effect for quarter (Jan-March, April-June, July-Sept, Oct-December). It absorbs changes that affect all CSPs equally in that quarter, such as macroeconomic conditions in England and Wales. Crucially, it also absorbs seasonal variations in hate crime, which could result in higher hate crimes in summer than in winter. η is the fixed effect for CSP, which absorbs time-invariant differences between CSPs. ϵ is the idiosyncratic error term. Since we measure hate crime and attitudes at the CSP level, we cluster the standard errors on CSP.

$\mathbf{X}$ is a vector of CSP level covariates that vary over time. Since hate crime may depend on changes in the size and composition of the population in a CSP, we include controls for population size, number of EU migrants, and number of non-EU migrants. Panel A of Table A.1 offers summary statistics on these variables. While conducting robustness checks, we consider additional variables to capture changes in the economic environment in post-event periods. These include household income, social benefits received, and taxes paid on income and wealth.

The coefficient of interest is β, which captures the effect of attitudes on hate crime in the Post-Event period. Our conceptual framework suggests β to have a counterintuitive positive sign. This is because the information shock from UKIP and Brexit events is expected to be larger in CSPs with more positive attitudes toward immigrants. This means, we expect a steeper rise in hate crime in CSPs with more positive attitudes toward immigrants.

While estimating β in response to the UKIP event, we restrict the sample to periods before Brexit, that is, from Q2 2002 to Q1 2016, otherwise we end up assigning the effect of Brexit to UKIP. We are aware that the estimates of β in the post-Brexit period might be underestimated if we fail to account for the surge in hate crime in the pre-Brexit period because of UKIP. So, we also present results from the estimation of equation (9) in which we include interaction of attitudes separately with UKIP and Brexit events.

The identifying assumption is that in the absence of the event, the evolution of hate crime will be similar between CSPs with weaker and stronger attitudes toward immigrants. We present several strategies below to mitigate concerns under which this assumption may be violated. This includes event studies using both UKIP and Brexit, accounting for confounding changes related to reporting of crime and economic condition.

IV.A. Event Study

We carry out event studies to examine the evolution of hate crime after UKIP and Brexit events separately below.

UKIP Event Study.– We examine the evolution of association between attitudes towards immigrants and hate crime before and after the UKIP election using the following equation:

$$\text{Hate}_{it} = \sum_{k=2002Q2}^{2016Q1} \beta_k \cdot T_{it}^k \times \text{Attitudes}_i + \gamma \mathbf{X}_{it} + \tau_t + \eta_i + \epsilon_{it} \tag{10}$$

where $\sum_{k=2002Q2}^{2016Q1}$ captures the time window of 48 quarters before the UKIP event (starting from Q2 2002) and eight quarters afterward, including zero (up to Q1 2016). T_{it}^k are indicators for the event-time quarters k. $k = 0$ is the quarter in which the European Parliament elections were held (Q2 2014). The omitted category ($k = -1$) is Q1 2014. The remaining terms are the same as in Equation (9).

Panel A of Figure 2 presents the result using the standardized measure of hate crime. Prior to the UKIP event, the evolution of hate crime in areas with less or more positive attitudes toward immigrants is very similar and stable over time. In contrast, in the period after the UKIP event, there is a steep rise in hate crime in areas with more positive attitudes towards immigrants. The coefficients turn out to be positive and are also individually and jointly statistically significant at the 1-percent level. This finding suggests that prior to the UKIP event, the trend in hate crime was similar across CSPs with less or more positive attitudes toward immigrants. However, in the post-UKIP period, the information shock led to stronger surge in hate crime in CSPs with more positive attitudes toward immigrants.

Brexit Event Study.– The second event study examines the evolution of association between attitudes towards immigrants and hate crime before and after the Brexit referendum using the following equation:

$$\text{Hate}_{it} = \sum_{k=2002Q2}^{2019Q4} \beta_k \cdot T_{it}^k \times \text{Attitudes}_i + \gamma \mathbf{X}_{it} + \tau_t + \eta_i + \epsilon_{it} \tag{11}$$

where $\sum_{k=2002Q2}^{2019Q4}$ captures the time window of 57 quarters before Brexit (starting from Q2 2002) and fourteen quarters afterward, including zero (up to Q4 2019). T_{it}^k are indicators for the event-time quarters k. Since the Brexit referendum took place on June 23, just one week before the end of Q2 2016, we choose this as the omitted category ($k = -1$), while $k = 0$ corresponds to the quarter immediately following the Brexit referendum (Q3 2016). The remaining terms are the same as in Equation (9).

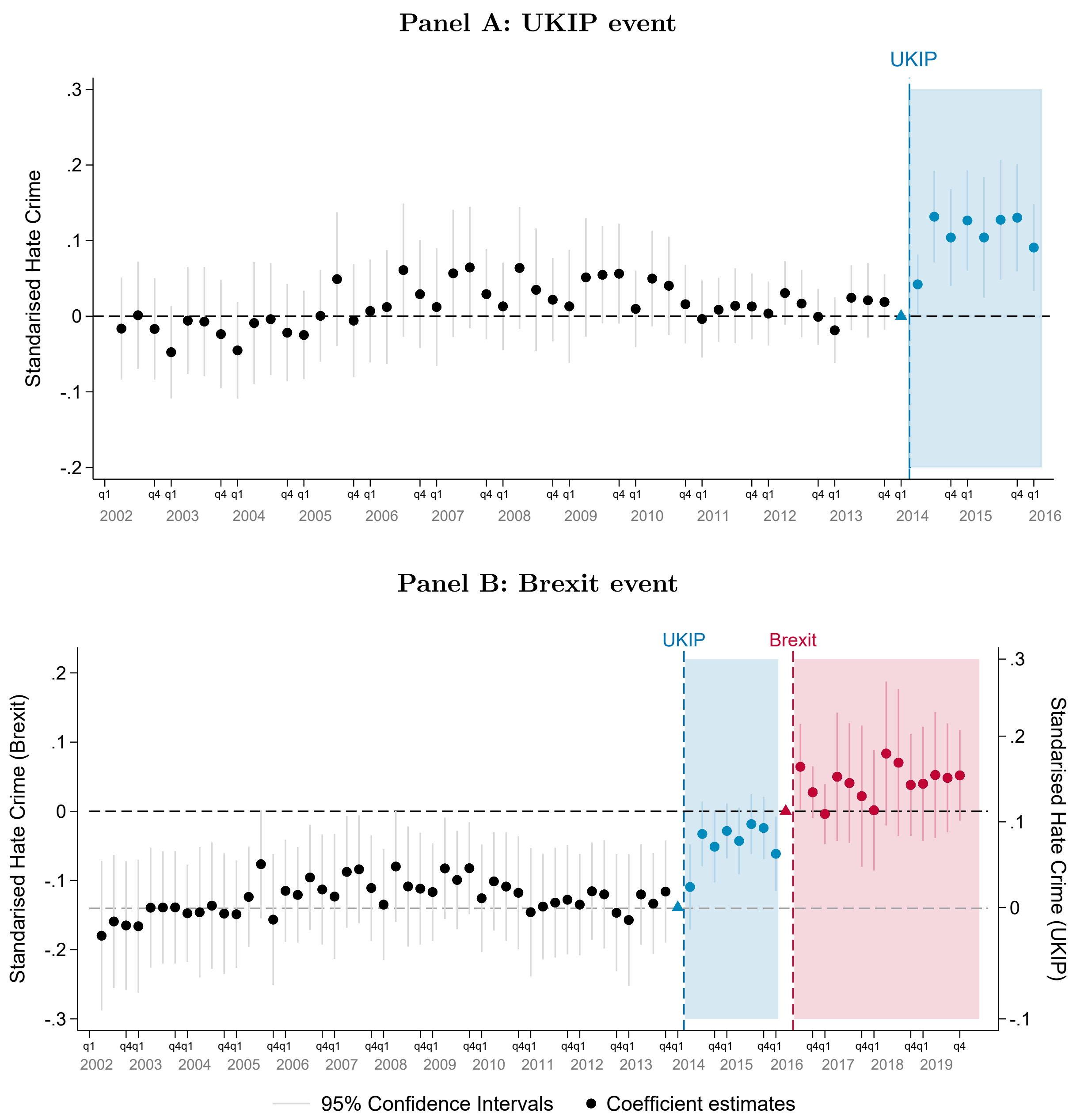


Figure 2: Event studies on the information shock of events on hate crime

Notes: Panel A plots coefficients on $T_{it}^{k} \times Attitudes$ from the estimation of equation 10, the UKIP event-study. The Y-axis is standardized measure of hate crime, black markers correspond to pre-UKIP period, blue markers correspond to post-UKIP event, the blue triangle corresponds to baseline (omitted) period of Q1 2014, and the blue vertical line corresponds to the UKIP election event. Panel B plots coefficients on $T_{it}^{k} \times Attitudes$ from the estimation of equation 11, the Brexit event-study. The primary Y-axis is standardized hate crime in all quarters that cover the Brexit event, red markers refers to post-Brexit event, the red triangle corresponds to baseline (omitted) period of Q2 2016 and the red vertical line corresponds to the Brexit referendum event. As a reference, in Panel B, we also highlight the UKIP event study using the secondary Y-axis. In both panels, in the X-axis, q1 refers to quarter 1, q4 to quarter 4, while q2 and q3 are omitted for space considerations. Ninety-five percent confidence intervals are constructed for standard errors clustered at the CSP level.

Panel B of Figure 2 presents the result using a standardized measure of hate crime, while also including a reference line for UKIP. We find a substantial and statistically significant increase in hate crime in the period after the Brexit event in CSPs with more positive attitudes toward immigrants (see the red solid circles). The effect peaks immediately after the Brexit referendum in Q3 2016 and remains on average higher than in the post-UKIP period.

IV.B. Confounding Changes

The event study bolsters our confidence on the absence of pre-trends in hate crime between CSPs with weaker and stronger attitudes towards immigrants. However, there could be concerns over confounding with other concurrent changes. We address these below.

Terrorist Attacks.– One concern could be the terrorist attacks that occurred in the second quarter of 2017 in London and Manchester, which were perpetrated by immigrants and individuals of foreign descent. If these attacks led to a surge in hate crime in CSPs with more positive attitudes towards immigrants, this could result in overestimation of the effect of information shock from Brexit. While there is no doubt that terrorist events like these generate shocks, it is highly likely that they have a direct bearing on attitudes towards immigrants or foreigners, who are now more likely to be perceived as a threat. Existing evidence argues that negative rhetoric about immigrants, foreigners and more generally minorities is more likely to be picked up by individuals with pre-existing prejudice.[11] This suggests that our estimates are, if anything, more likely to be downward rather than upward biased. Nevertheless, we present results in which we control for a post-indicator for Q2 of 2017 interacted with attitudes to account for changes in hate crime due to terrorist attacks.

Economic Conditions.– Fetzer (2019) shows that poor economic conditions combined with austerity were responsible for the rise in UKIP popularity and support for Brexit. Therefore, one concern could be that the surge in hate crime in the post-event period is not because of information shock from UKIP or Brexit but is actually due to the persistent effect of economic conditions from the pre-event periods. However, an empirical regularity observed across many countries is that areas with poor economic conditions tend to be associated with less rather than more tolerant attitudes toward immigrants. This is also what we observe in our data, where the correlation between attitudes towards immigrants and gross disposable household income is positive and statistically significant ($r = 0.56$, p-value <0.001). In this situation, it is the CSPs with negative and not positive attitudes toward immigrants that are expected to witness a surge in hate crime in the post-event

[11] For example, Maja Adena, Ruben Enikolopov, Maria Petrova, Veronica Santarosa and Ekaterina Zhuravskaya (2015) and Nico Voigtländer and Hans-Joachim Voth (2015) show that Nazi antisemitic rhetoric in pre-World War II Germany had a stronger impact in areas with pre-existing antisemitic sentiment. Leonardo Bursztyn, Georgy Egorov, Ruben Enikolopov and Maria Petrova (2019) and Karsten Müller and Carlo Schwarz (2019) similarly find that exposure to xenophobic propaganda on social media has a stronger effect on xenophobic hate crime in pre-existing nationalistic areas.

period. Thus, it is highly unlikely that our estimates are confounded with pre-existing economic conditions.

A related concern could be that the surge in hate crime is the result of poor economic conditions arising from the events themselves. Notice, however, that the patterns in Figure 1 clearly show an immediate rise in hate crime in the post-event periods. This means that this concern is plausible only if economic outcomes also changed immediately after the events. However, this seems unlikely because the evidence suggests that changes in economic outcomes occurred with a lag of several months. In fact Bakker et al. (2022) show that consumer prices remained unchanged right after the referendum in 2016.

Nonetheless, it is conceivable that the effect, especially in later periods after the event, might be in part due to post-event changes in economic conditions. We adopt two strategies to deal with this. First, to the extent that changes in economic conditions occur at the regional level, we account for such changes by controlling for region-specific time trends. Second, while conducting robustness checks, we control for three additional proxies of changes in economic conditions: social benefits received, gross disposable household income, and taxes on income and wealth. Panel B of Table A.1 reports the summary statistics on these variables.

Recording of Hate Crime.– Another potential concern could be changes in the recording of hate crimes in CSPs. This would require that changes in recording occur disproportionately in CSPs with more positive attitudes toward immigrants. We consider two strategies to deal with this concern. First, recording practices may have changed during the pre-event periods, but the effect persists in the post-event periods. To address this concern, we control for police force-specific time trends. There are 42 police force units covering the CSPs in our sample. Thus, to the extent that there are changes in recording by police force over time, we control for this. Second, police recording practices may have changed in the post-event period, especially due to increased sensitivity among the police or directives to record hate crimes more accurately. To address this concern, we control for an interaction between the post-event indicator and the police force. This allows us to account for changes in recording that may have resulted from the events themselves.

Falsification Test using Other Crimes.– The information shocks from the UKIP and Brexit events should not affect crimes such as murder, burglary, and driving violations. However, there could be a surge in all of these crimes due to changes in economic conditions as well as reporting practices. Accordingly, we construct falsification tests using data on these crimes to confirm that our results are not spurious. We do not expect substitution between hate crime and other crimes unless murder, burglary, and driving violations were specifically targeted towards immigrants, which seems unlikely. Nevertheless, while conducting robustness checks we control for these crimes.

V. Results

We begin by presenting our main results followed by a variety of robustness checks.

V.A. Main Result

Table 1 reports our main results, which we present separately for the UKIP event in Panel A and Brexit event in Panel B. Column 1 includes only fixed effects for quarter and CSPs. We find that one standard deviation increase in attitudes toward immigrants (0.458) is associated with a rise in hate crime in the post-UKIP period by 0.159 standard deviations and post-Brexit period by 0.15 standard deviations. These estimates are not only economically meaningful but are also statistically significant at the 1-percent level.

Table 1: Information Shock, Attitudes, and Hate Crime

	Dependent Variable: Standardized Hate Crime				
	Quarter & CSP FE	With Controls	Region x Time Trend	Police x Time Trend	Police x Post-Event
	(1)	(2)	(3)	(4)	(5)
	Panel A: UKIP Event				
Post-UKIP × *Attitudes*	0.159	0.143	0.094	0.105	0.110
	(0.023)	(0.022)	(0.021)	(0.019)	(0.019)
R^2	0.89	0.90	0.91	0.93	0.90
Observations	17,024	17,024	17,024	16,912	17,024
	Panel B: Brexit Event				
Post-Brexit × *Attitudes*	0.150	0.090	0.122	0.143	0.156
	(0.036)	(0.027)	(0.032)	(0.031)	(0.032)
R^2	0.86	0.87	0.89	0.92	0.89
Observations	21,577	21,577	21,577	21,435	21,577
Number of CSPs	304	304	304	302	304
CSP Fixed Effects	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Region × Quarter	No	No	Yes	No	No
Police × Quarter	No	No	No	Yes	No
Police × Post-Event	No	No	No	No	Yes

Notes: OLS estimates with standard errors clustered by CSP. FE stands for fixed effects. Control variables include population, number of EU migrants, and number of Non-EU migrants. Attitudes is toward immigrants and is standardized to have have mean of zero and standard deviation of 1. Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column (4) has fewer observations because two CSPs have singleton observations.

In column 2, we introduce controls for population size, number of EU immigrants, and number of non-EU immigrants. The coefficient on the interaction term declines in magnitude to 0.143 in Panel A and to 0.09 in Panel B, but so does its standard error. As a result, the coefficients remain statistically significant at the 1-percent level. The control variables are jointly statistically significant at 5-percent level.

In column 3, we control for region-specific time trends to account for regional differences in macroeconomic changes over time. In Panel A, the coefficient on the interaction term declines in magnitude to 0.094, but remains statistically significant at the 1-percent level. In contrast, in Panel B, it rises in magnitude to 0.122 and retains its statistical significance.

In column 4, we introduce police force-specific time trends to account for possible changes in crime recording behavior. In both panels, the coefficient increases slightly in magnitude and its standard error declines. Finally, in column 5, we control for an interaction between police force and post-event indicator to account for possible changes in crime recording behavior that may have been induced by the event itself. The coefficients increase slightly in magnitude and remain highly statistically significant.

Overall, a one-standard deviation increase in attitudes toward immigrants is associated with a rise in hate crime by 0.09-0.16 standard deviations in response to the information shock from the UKIP and Brexit events.

V.B. Robustness

We carry out a number of robustness checks reported below, which confirm our main results. For this purpose, we use the specifications with our full set of controls in columns 3-5 of Table 1.

Log of Hate Crime.– Table A.2 reports results using log transformation of hate crime. Panel A shows that regardless of the specification, one percent increase in attitudes in the Post-UKIP period is associated with a rise in hate crime by 6-7 percent, which is statistically significant at the 1-percent level. Similarly, Panel B shows that the corresponding rise in hate crime in the Post-Brexit period ranges between 6-9 percent and is also statistically significant at the 1-percent level.

Additional Economic Variables.– Our results are also robust to introducing three additional economic variables: gross disposable household income, average amount of social benefits received, average of current taxes paid on income and wealth. Since these variables are highly correlated ($r > 0.88$), we introduce them one at a time. Our results hold in magnitude and significance when we control for Gross Disposable Household Income (GDI) in Table A.3, Taxes on income and wealth in Table A.4 and Social Benefits Received in Table A.5.

Using One Attitude at a Time.– So far, our results are based on attitudes measured using an average of two questions from BES. Table A.6 shows that our results are robust to using measures of attitudes based on one survey item at a time. Columns 1-3 report results using the survey question reflecting economic considerations "Do you think immigration is good or bad for Britain's economy?". Columns 4-6 report results using the survey question reflecting cultural considerations "Do you think that immigration undermines or enriches Britain's cultural life?". Regardless of the question we use, the coefficients on attitudes in the post-event periods pertaining to both UKIP and Brexit are comparable in magnitude to the results presented before and retain their statistical significance at the 1-percent level.

Alternative Wave to Measure Attitudes.– So far, our results are based on attitudes measured using questions from Wave 1 for UKIP and Wave 8 for Brexit. For the Brexit event, we can test whether our results hold when we use responses to the same questions from Wave 7, which was conducted two months before Brexit. We are unable to carry out this exercise for the UKIP event because there is only one survey wave that was conducted before this event. Table A.7 reports the results. The coefficient is similar in magnitude and statistical significance to that reported in Table 1.

Falsification Test using Other Crimes.– We provide further evidence in support of our results by conducting a falsification test using data on other crimes (murder, burglary, driving fines). These crimes are unlikely to be affected by information shocks but may change in response to other confounding changes, such as those related to recording crime or deterioration in the economic environment. Table A.8 shows the results, whereby the dependent variable is the aggregation of other crimes, which we standardized to have a mean of zero and standard deviation of 1. Results in both panels show that the effect of attitudes on other crimes in the post-event period is always negative, which is the opposite of what we observe for hate crime. Though the coefficient is statistically significant, it is much smaller in magnitude to the one we observe in the regression of hate crime. We also test the robustness of our results to controlling for other crimes. Table A.9 shows that this has no effect on our findings as the coefficient of post-even x attitudes remains positive and statistically significant throughout.

Simultaneously Considering UKIP and Brexit Events.– So far, we estimate the effect of attitudes on hate crime separately for the two events. We test whether our results hold when we include both interaction terms simultaneously. Table A.10 reports the results. We find that the coefficient on *post-UKIP* $\times$ *attitudes* ranges from 0.067 – 0.106, and is always statistically significant. The corresponding estimate for *post-Brexit* $\times$ *attitudes* ranges from 0.077 – 0.086 and is also always statistically significant.

VI. Mechanism

Thus far, our results show a robust positive link between attitudes toward immigrants and hate crime in the post-event period. Why do we find such a counterintuitive result? As discussed in Section II, this is because in the pre-event period, individuals lack information on the country-wide distribution of attitudes toward immigrants and believe these to be similar to the distribution found in their CSP. However, events like the UKIP election and the Leave camp victory in the Brexit referendum generate new information on the country-wide distribution of such attitudes. This results in a belief shock for individuals from CSPs with more tolerant attitudes on average, as they expect the country to be tolerant just like their CSP. Crucially, individuals from more tolerant CSPs respond to this belief shock in a heterogeneous manner. In particular, individuals with xenophobic attitudes feel emboldened and resort to hate crime, as they now know that their own attitudes align with that of the majority in the country. In contrast, as expected, individuals with more tolerant attitudes do not resort to hate crime despite experiencing the belief shock.

In our context, we expect UKIP election to serve as the first shock, followed by a second shock triggered by the Brexit event. One might argue that after UKIP there should be no shock as the xenophobic people from more tolerant CSPs already know the distribution of xenophobia in the country from the UKIP event. However, voter turnout in the Brexit referendum was clearly much larger than in the European Parliament elections of 2014 (72% vs 35% of registered voters), implying that the information it released about attitudes in the country as a whole was more accurate. This suggests that Brexit served as further, and stronger shock and hence led to a further rise in hate crime.

Testing this mechanism warrants data on prior beliefs about the likelihood of an event happening. The BES offers data on prior beliefs only for the likelihood of Brexit happening, whereas data on the likelihood of UKIP victory were only collected ex post. In view of this limitation, we view results on belief shock from UKIP election as demonstrating not a definite but a proof-of-concept for underlying mechanism. We uncover the mechanism in three steps presented below.

VI.A. Attitudes and Belief Shock

We start by showing at the individual level a positive association between between attitudes towards immigrants and beliefs shocks.

Data.– To construct measures of belief shock, we use data on beliefs from the British Election Study (BES). For the UKIP election, we use responses in Waves 4 and 5, which were conducted between 4 March 2015 and 6 May 2015, 10-12 months after the UKIP election. In the study, individuals were asked the question "Which of these parties do you think has [NO] real chance of being part of the next UK government?" UKIP appeared as one of the listed political parties. Respondents answered using a binary option, with 0 indicating "No" and 1 indicating "Yes". We measure belief shock as 1 minus the perceived chance of UKIP winning (Yes). The average turns out to be 36.5%. Note that this measure captures belief shock after the event and only at the extensive margin, so we expect this measure to be biased downwards.

The data on beliefs about Brexit happening are from wave 8 of BES, which was conducted between 6 May 2016 and 22 June 2016, just a month before the Brexit referendum. In the survey, individuals were asked to rate the likelihood that Brexit will happen on a scale of 0-100, where 0 implies that "UK will definitely vote to remain" and 100 implies "UK will definitely vote to leave". Since the Leave campaign won the Brexit referendum, we measure belief shock as 100 minus the perceived likelihood of the Leave campaign winning. The average belief shock is 48.7%.

Results.– The descriptive results in Figure 3 show a strong positive associated between attitudes toward immigrants and belief shocks from UKIP (left) and Brexit (right). This suggests that individuals with more tolerant attitudes toward immigrants are also the ones who experience larger belief shocks from the events.

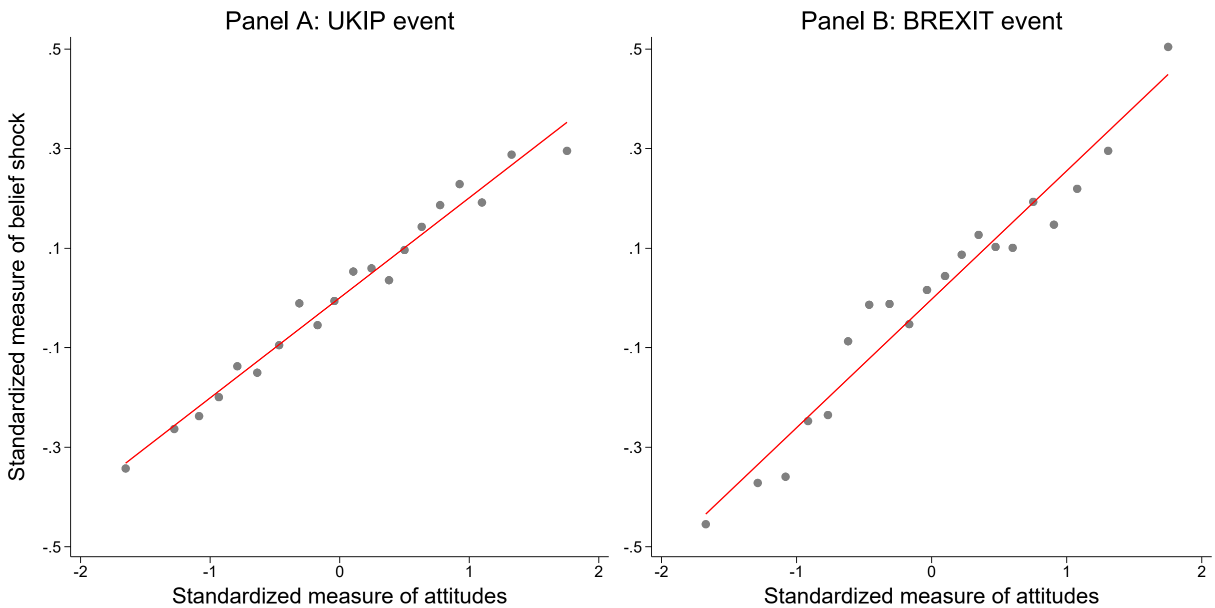


Figure 3: Belief shock and attitudes

Notes. Figure shows the association between attitudes toward immigrants and belief shock from UKIP (left) and from Brexit (right). All variables are standardized to have a mean of 0 and standard deviation of 1. Data are at the individual level from BES.

We test whether these patterns are robust in Panels A-B of Table 2. Column 1 is without any controls, column 2 introduces individual level controls (age, gender, education, gross household income, religion, and ethnicity), and column 3 includes CSP level controls (population, number of EU migrants, and number of non-EU migrants). The coefficients on attitudes in both panels are statistically significant at the 1-percent level. The magnitude of the coefficients implies that one standard deviation increase in attitudes toward immigrants is associated with a rise in belief shock by 0.19-0.20 percentage points for UKIP and 0.26-0.30 standard deviations for Brexit. Together, these findings suggest that individuals with more tolerant attitudes toward immigrants experienced larger belief shocks.

Table 2: Attitudes toward Immigrants and Belief Shock

	Dependent Variable: Standardized Belief Shock		
	Without controls (1)	Individual controls (2)	Individual & CSP controls (3)
	Panel A: UKIP Event		
Attitudes towards Immigrants	0.192	0.202	0.201
	(0.007)	(0.009)	(0.009)
R^2	0.04	0.05	0.05
Observations	20,427	17,409	17,409
	Panel B: Brexit Event		
Attitudes towards Immigrants	0.303	0.258	0.257
	(0.007)	(0.008)	(0.008)
R^2	0.09	0.11	0.11
Observations	23,818	20,170	20,170
Number of CSPs	304	304	304
Individual Controls	No	Yes	No
CSP Controls	No	No	Yes

Notes: OLS estimates with standard errors clustered by CSP. Both belief shock and attitudes towards immigrants are standardized with mean zero and standard deviation of one. Individual controls include household income, age, gender, education level, ethnicity and religion. CSP controls include population, number of EU migrants, and number of Non-EU migrants. All specifications incorporate year and CSP fixed effects. Data are at the individual level from BES.

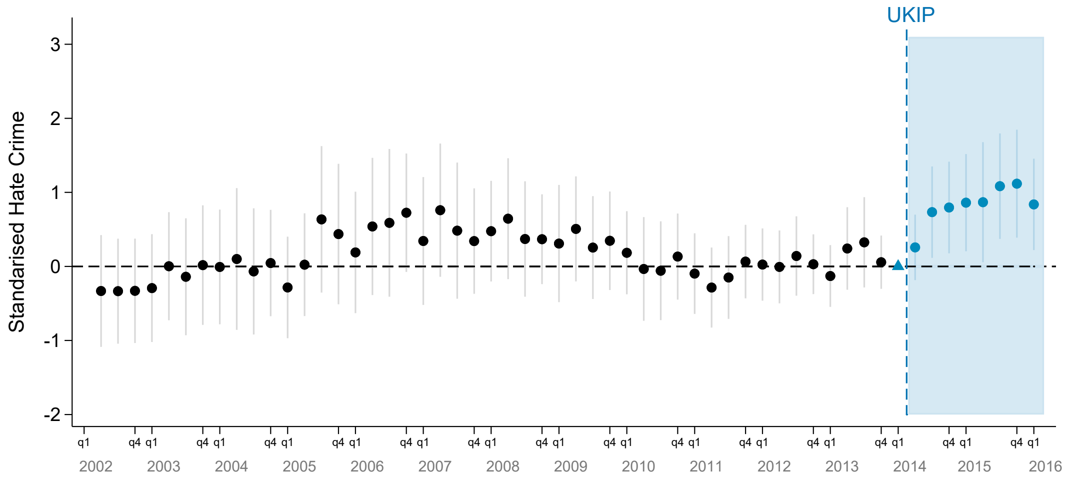
VI.B. Beliefs Shocks and Hate Crime in Post-Event Periods

Next, we examine if belief shocks are associated with hate crime in the post-event period. Since the data on hate crime are not available at the individual level, we carry out this exercise at the CSP level.

The event studies in Figure 4 reveal a strong positive association between belief shocks and hate crime in the both post-event periods. Table 3 present results from an econometric analysis using the same specifications as in Table 1. Column 1 includes only CSP and quarter fixed effects. It shows that one-standard deviation increase in belief shock is associated with a rise in hate crime by 0.08 standard deviations for UKIP and 0.12

standard deviations for Brexit. In columns 2-5, we sequentially introduce the remaining controls. Panel A shows that the coefficient on belief shock in the post-UKIP period declines in magnitude from 0.083 in column 1 to 0.032 in column 5. Nonetheless, it remains significant at least at the 5 percent level. This is likely because the data on beliefs shocks from the UKIP event are based on post-event period and are measured only at the extensive margin.

Panel A: UKIP event



Panel B: Brexit event

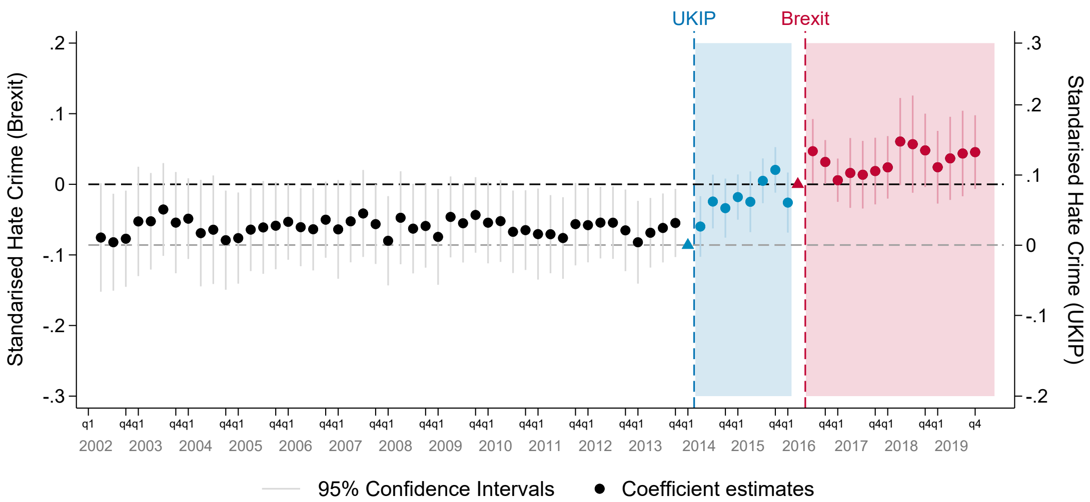


Figure 4: Event Study on Belief Shock and Hate Crime

Notes: This graph displays the result of an event-study after estimating equations 10 and 11. The coefficients are based on *Belief shock*$\times T_{it}^{k}$, where T_{it}^{k} are event-time indicators that the event happened k quarters away from UKIP and Brexit events. Black markers refer to pre-UKIP period, blue markers correspond to post-UKIP event, red marker refers to post-Brexit event, and triangles are the omitted benchmark categories for both UKIP and Brexit. The baseline period is 2014 Q1 for UKIP and 2016 Q2 for Brexit. On the X-axis, q1 refers to quarter 1, q4 to quarter 4, while q2 and q3 are omitted for space considerations. Ninety-five percent confidence intervals are constructed for standard errors clustered at the CSP level.

Table 3: Belief Shock and Hate Crime

	Dependent Variable: Standardized Hate Crime				
	Quarter & CSP FE	Time Varying Controls	Region x Time Trend	Police x Time Trend	Police x Post-Event
	(1)	(2)	(3)	(4)	(5)
	Panel A: UKIP Event				
Post-UKIP × Belief Shock	0.083	0.072	0.045	0.030	0.032
	(0.018)	(0.016)	(0.013)	(0.015)	(0.014)
R^2	0.89	0.90	0.91	0.93	0.90
Observations	17,024	17,024	17,024	16,912	17,024
	Panel B: Brexit Event				
Post-Brexit × Belief Shock	0.107	0.062	0.070	0.079	0.072
	(0.030)	(0.026)	(0.026)	(0.027)	(0.028)
R^2	0.86	0.87	0.89	0.92	0.89
Observations	21,577	21,577	21,577	21,435	21,577
Number of CSPs	304	304	304	302	304
CSP FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Region × Time Trend	No	No	Yes	No	No
Police × Time Trend	No	No	No	Yes	No
Police × Post-Event	No	No	No	No	Yes

Notes: OLS estimates with standard errors clustered by CSP. FE stands for fixed effects. Control variables are at the level of CSP and include population, number of EU migrants, and number of Non-EU migrants. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column (4) has fewer observations because two CSPs have singleton observations.

In contrast, Panel B shows that the coefficient on belief shocks in the post-Brexit period remains close to 0.07 in magnitude and is always statistical significant at the 1-percent level. The magnitude of these coefficients imply that one-standard deviation increase in belief shocks are associated with an increase in hate crime by 0.03 standard deviations in the post-UKIP period and by 0.07 standard deviations in the post-Brexit period. These results hold when we control one at a time for GDI (Table A.11), Taxes on Income and Wealth (A.12), and Social Benefits Received (Table A.13).

VI.C. Attitudes, Belief Shock, and Xenophobic Behavior in Post-Event Periods

The CSP level results mask an heterogeneity concerning the type of individuals who engage in hate crime in more tolerant CSPs. Since hate crime data are not available at the individual level, we carried out an original survey in which we attempt to link attitude, beliefs, and tendency to engage in xenophobic behavior. Our purpose here is to show that in more tolerant CSPs, it is the xenophobic people who engage in hate behavior and not the liberal ones. We present two pieces of supporting evidence.

First, we show that the positive association between attitudes towards immigrants in a CSP and belief shock holds even when we restrict the analysis to individuals whose attitudes towards immigrants falls below the sample median. We refer to these individuals as "xenophobic." Table 4 reports the results without controls in column 1, individual level controls in column 2, and CSP level controls in column 3. Regardless of the specification, the coefficient on attitudes is always positive, robust in magnitude, and statistically significant at the 1 percent level. These results imply that xenophobic individuals living in more tolerant CSPs experience a greater belief shock than xenophobic individuals living in less tolerant CSPs. The magnitude of the coefficient implies that one standard deviation increase in attitudes is associated with a rise in belief shock by 0.04-0.06 s.d.

Table 4: Attitudes and Belief Shock among Xenophobic Individuals

	Dependent variable: Standardized Belief Shock		
	Without Controls (1)	Individual Controls (2)	Individual & CSP Controls (3)
	Panel A: UKIP Event		
Attitudes towards Immigrants	0.050	0.048	0.049
	(0.010)	(0.010)	(0.012)
Observations	12,131	10,230	10,230
	Panel B: Brexit Event		
Attitudes towards Immigrants	0.061	0.036	0.039
	(0.009)	(0.009)	(0.011)
Observations	14,320	12,052	12,052
Number of CSPs	304	304	304
Individual Controls	No	Yes	Yes
CSP Controls	No	No	Yes

Notes: OLS estimates with standard errors clustered by CSP. Attitudes towards immigrants are measured as CSP average in the full sample. The sample is restricted to xenophobic individuals only, who are defined as those who attitudes fall below the median attitude in the full sample. Individual controls include household income, age, gender, education level, ethnicity and religion. CSP controls include population, number of EU migrants, and Non-EU migrants. All variables are standardized with median zero and standard deviation of one.

Second, we show that individuals who dislike immigrants and live in CSPs with more tolerant attitudes are also the ones who are more likely to express their views about immigrants following the Brexit referendum. Table 5 shows that xenophobic individuals living in liberal areas are more likely to increase their expression of views on immigrants after the Brexit referendum than those living in less liberal areas. The reason being that xenophobic individuals in liberal areas experienced a belief shock, whereas those in more xenophobic areas did not.

Table 5: **Changes in vocalizing views on immigrants**

	Dependent variable: Change in Expression	
	Without controls (1)	With controls (2)
Individual Xenophobia	0.062	0.035
	(0.052)	(0.052)
Tolerance CSP	-0.057	-0.065
	(0.045)	(0.045)
Individual Xenophobia × Tolerance CSP	0.194	0.196
	(0.049)	(0.049)
R^2	0.055	0.066
Observations	1,635	1,635
Controls	No	Yes

Notes: OLS estimates with standard errors clustered by individual. The dependent variable "Change in expression" is toward immigrants and measures the change in how likely respondents are to express their opinions on immigrants following the Brexit referendum. "Tolerance CSP" indicates the average attitudes toward immigrants at CSP level, higher values indicate more tolerant area. "Individual Xenophobia" captures respondent's own views on immigrants, with higher values reflecting more xenophobic attitudes. Controls include household age, gender, education level, income and employment. Tolerant CSP × Xenophobic Individual is the interaction term that captures how the effect of an individual's xenophobic attitude on expressing views on immigrants changes as the local context varies. All variables are standarised with media zero and standard deviation of one.

VII. Conclusion

In this paper we study the impact of information shocks resulting from the unexpected UKIP event in the European Parliament elections and the Brexit referendum on xenophobic behavior in England and Wales. By analyzing data from all Community Safety Partnerships (CSPs) between the second quarter of 2002 and the fourth quarter of 2016, and incorporating individual-level attitudes toward immigrants from the British Election Study, we employ a difference-in-differences approach to uncover the causal relationship between attitudes and hate crimes following these important events.

Our theoretical framework suggests that the information shocks from UKIP and Brexit were more pronounced for xenophobic individuals living in CSPs where positive attitudes toward immigrants are prevalent. Consistent with this hypothesis, our empirical findings reveal a strong positive association between positive attitudes toward immigrants and a surge in hate crimes in the post-Brexit period. Specifically, a one standard deviation increase in positive attitudes toward immigrants is associated with a 0.11 standard deviation rise in hate crimes following the UKIP event and a 0.20 standard deviation rise after the Brexit referendum. This relationship holds even after controlling for population size, the proportion of EU and non-EU immigrants, seasonal fixed effects, and introducing region and police force-specific time trends.

To ensure the robustness of our results, we conducted several checks. We used other crimes—such as murder, burglary, and driving offenses—as placebos and found no significant association, indicating that our findings are not spurious. Additionally, our results remained consistent when using alternative waves to measure attitudes toward immigrants and when accounting for potential changes in reporting behavior.

Consistent with our theoretical framework, we also show that the belief shock is larger for individuals living in areas where positive attitudes toward immigrants dominate. Using data on individuals' perceived likelihood of Brexit occurring, we found a positive association between attitudes toward immigrants and belief shock. When replacing attitudes with belief shock in our main specification, we still get a positive association with the surge in hate crimes.

Our study sheds light on the complex dynamics between individual beliefs, local social norms, and national-level information shocks. The findings suggest that unexpected national events can significantly influence xenophobic behavior, particularly in areas where local attitudes are more welcoming toward immigrants. This has important implications for policymakers aiming to foster social cohesion and address hate crimes.

Future research could explore the long-term effects of such information shocks on community relations and examine the effectiveness of interventions designed to mitigate the adverse impacts on minority groups.

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ONLINE APPENDIX:
Updating the social norm

Appendix A

Summary Statistics

Panel A: Main Variables	
Hate Crime	31.963
	(43.407)
Attitudes Toward Immigrants	3.636
	(0.458)
Population	180.304
	(118.067)
Number of EU migrants	271.197
	(452.551)
Number of Non-EU migrants	177.304
	(329.212)
Panel B: Additional Variables	
Social Benefits Received	849.067
	(598.268)
Gross Disposable Household Income	3,200.263
	(2281.152)
Taxes on income and wealth	569.740
	(479.241)

Notes: The table reports the mean of variables and standard deviations in parentheses. The panel covers up to 21,577 Community Safety Partnership (CSP) $\times$ quarter observations for 304 CSP areas in England and Wales over 2002 Q1–2019 Q4. Total Hate Crime is the count of police-recorded hate offences; it includes incidents that did not necessarily lead to charges or prosecution. Attitudes towards immigrants is an index constructed from BES questions (see Section III.B. for details). Population is the ONS mid-year estimate and is expressed in thousands. Migrant flows are measured by quarterly National Insurance Number (NINO) registrations, split into EU and non-EU nationals. Social benefits received, gross disposable household income (GDI) and taxes on income and wealth are expressed in millions of nominal pounds (£).

Table A.2: Information Shock, Attitudes, and Hate Crime
Log of Hate Crime

	Dependent Variable: Log Hate Crime		
	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)
	Panel A: UKIP event		
Post-UKIP × *Attitudes*	0.058	0.066	0.068
	(0.019)	(0.014)	(0.013)
R^2	0.87	0.900	0.86
Observations	17,024	16,912	17,024
	Panel B: BREXIT event		
Post-Brexit × *Attitudes*	0.066	0.066	0.087
	(0.021)	(0.018)	(0.018)
R^2	0.87	0.91	0.87
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP fixed effects	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. The dependent variable is log of hate crime. Control variables are also expressed in logs; these include population, number of EU migrants, and number of Non-EU migrants. Attitudes toward immigrants is also expressed in logs. Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column 2 has fewer observations because two CSPs have singleton observations.

Table A.3: Information Shock, Attitudes, and Hate Crime:
Controlling for GDI

	Dependent Variable: Standardized Hate Crime		
	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)
	Panel A: UKIP Event		
Post-UKIP × *Attitudes*	0.081	0.088	0.106
	(0.019)	(0.018)	(0.019)
GDI	0.305	0.330	0.110
	(0.066)	(0.078)	(0.060)
R^2	0.91	0.93	0.90
Observations	17,024	16,912	17,024
	Panel B: BREXIT Event		
Post-Brexit × *Attitudes*	0.102	0.111	0.144
	(0.029)	(0.027)	(0.031)
GDI	0.484	0.571	0.373
	(0.137)	(0.142)	(0.103)
R^2	0.90	0.92	0.89
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Attitudes is toward immigrants and is standardized to have have mean of zero and standard deviation of 1. Control variables include population, number of EU migrants, number of Non-EU migrants. Additional economic variable includes gross disposable household income. This variable is expressed in millions of nominal pounds (£). Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column 2 has fewer observations because two CSPs have singleton observations.

Table A.4: Information Shock, Attitudes, and Hate Crime:
Controlling for Taxes Paid

	Dependent Variable: Standardized Hate Crime		
	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)
	Panel A: UKIP Event		
Post-UKIP × *Attitudes*	0.080	0.088	0.106
	(0.020)	(0.019)	(0.019)
Taxes paid	0.245	0.270	0.101
	(0.061)	(0.071)	(0.048)
R^2	0.91	0.93	0.90
Observations	17,024	16,912	17,024
	Panel B: BREXIT Event		
Post-Brexit × *Attitudes*	0.097	0.113	0.143
	(0.031)	(0.029)	(0.032)
Taxes paid	0.311	0.322	0.219
	(0.113)	(0.117)	(0.093)
R^2	0.90	0.92	0.89
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Attitudes is toward immigrants and is standardized to have have mean of zero and standard deviation of 1. Control variables include population, number of EU migrants, number of Non-EU migrants. Additional economic variable includes current taxes paid on income and wealth. This variable is expressed in millions of nominal pounds (£). Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column 2 has fewer observations because two CSPs have singleton observations.

Table A.5: Information Shock, Attitudes, and Hate Crime:
Controlling for Benefits Received

	Dependent Variable: Standardized Hate Crime		
	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)
	Panel A: UKIP Event		
Post-UKIP × *Attitudes*	0.096	0.105	0.111
	(0.020)	(0.019)	(0.019)
Benefits Received	0.079	0.015	0.011
	(0.056)	(0.073)	(0.053)
R^2	0.91	0.93	0.90
Observations	17,024	16,912	17,024
	Panel B: BREXIT Event		
Post-Brexit × *Attitudes*	0.122	0.144	0.156
	(0.033)	(0.031)	(0.032)
Benefits Received	0.021	0.026	-0.022
	(0.090)	(0.106)	(0.072)
R^2	0.89	0.92	0.89
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Attitudes is toward immigrants and is standardized to have have mean of zero and standard deviation of 1. Control variables include population, number of EU migrants, number of Non-EU migrants. Additional economic variable includes social benefits received. This variable is expressed in millions of nominal pounds (£). Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column 2 has fewer observations because two CSPs have singleton observations.

Table A.6: Information Shock, Attitudes, and Hate Crime:
Using Attitudes Measures Separately

	Dependent Variable: Standardized Hate Crime					
	Immigration is Good For Economy			Immigration Enriches Cultural Life		
	Region × Time Trend	Police × Time Trend	Police × Post-Event	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: UKIP event					
Post-UKIP × *Attitudes*	0.086	0.101	0.107	0.095	0.102	0.107
	(0.020)	(0.019)	(0.018)	(0.021)	(0.020)	(0.019)
R^2	0.91	0.93	0.90	0.91	0.93	0.90
Observations	17 024	16 912	17 024	17 024	16 912	17 024
	Panel B: BREXIT event					
Post-Brexit × *Attitudes*	0.121	0.139	0.154	0.122	0.145	0.155
	(0.032)	(0.031)	(0.034)	(0.031)	(0.029)	(0.030)
R^2	0.89	0.92	0.89	0.89	0.92	0.89
Observations	21 577	21 435	21 577	21 577	21 435	21 577
Number of CSPs	304	302	304	304	302	304
CSP Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region × Time Trend	Yes	No	No	Yes	No	No
Police × Time Trend	No	Yes	No	No	Yes	No
Police × Post-Event	No	No	Yes	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Control variables include population, number of EU migrants, and number of non-EU migrants. In columns 1-3 attitudes toward immigrants are measured using the question "Do you think immigration is good or bad for Britain's economy?". In columns 4-6 attitudes toward immigrants are measured using the question "Do you think that immigration undermines or enriches Britain's cultural life?". In all columns attitudes are standardized to have mean 0 and standard deviation 1. Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Columns 2 and 5 have fewer observations because two CSPs have singleton observations.

Table A.7: Information Shock, Attitudes, and Hate Crime:
Results using Attitudes from Wave 7

	Dependent variable: Standardized hate crime		
	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)
Post-Brexit × *Attitudes*	0.105	0.129	0.138
	(0.029)	(0.027)	(0.031)
R^2	0.89	0.92	0.89
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Control variables include population, number of EU migrants, and number of Non-EU migrants. Attitudes toward immigrants are measured using wave 7 of BES. Column 2 has fewer observations because two CSPs have singleton observations.

Table A.8: Information Shock, Attitudes, and Other Crimes
Falsification Test

	Dependent Variable: Standardized Other Crimes		
	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)
	Panel A: UKIP event		
Post-UKIP × *Attitudes*	-0.039	-0.039	-0.048
	(0.018)	(0.018)	(0.016)
R^2	0.93	0.95	0.90
Observations	17,024	16,912	17,024
	Panel B: BREXIT event		
Post-Brexit × *Attitudes*	-0.026	-0.026	-0.042
	(0.015)	(0.017)	(0.017)
R^2	0.92	0.95	0.90
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP fixed effects	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Other crimes is the aggregation of murder, burglary and driving fines. It is standardized to have a mean of zero and standard deviation of 1. Control variables include population, number of EU migrants, and number of Non-EU migrants. Attitudes is toward immigrants and is standardized to have have mean of zero and standard deviation of 1. Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column 2 has fewer observations because two CSPs have singleton observations.

Table A.9: Information Shock, Attitudes, and Hate Crime
Controlling for Other Crimes

	Dependent Variable: Standardized Hate Crime		
	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)
	Panel A: UKIP event		
Post-UKIP × *Attitudes*	0.090	0.102	0.105
	(0.020)	(0.019)	(0.019)
Other Crimes	-0.095	-0.080	-0.112
	(0.043)	(0.043)	(0.044)
R^2	0.91	0.93	0.90
Observations	17,024	16,912	17,024
	Panel B: BREXIT event		
Post-Brexit × *Attitudes*	0.119	0.141	0.152
	(0.032)	(0.030)	(0.033)
Other Crimes	-0.092	-0.103	-0.095
	(0.050)	(0.051)	(0.036)
R^2	0.89	0.92	0.89
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP fixed effects	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Other crimes is the aggregation of murder, burglary and driving fines. It is standardized to have a mean of zero and standard deviation of 1. Control variables include population, number of EU migrants, and number of Non-EU migrants. Attitudes is toward immigrants and is standardized to have have mean of zero and standard deviation of 1. Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column 2 has fewer observations because two CSPs have singleton observations.

Table A.10: Information Shock, Attitudes, and Hate Crime:
Marginal Effect of UKIP and Brexit

	Dependent Variable: Standardized Hate Crime		
	Region × Time Trend (1)	Police × Time Trend (2)	Police × Post-Event (3)
Post-UKIP × *Attitudes*	0.067	0.084	0.106
	(0.021)	(0.021)	(0.019)
Post-Brexit × *Attitudes*	0.077	0.086	0.086
	(0.030)	(0.028)	(0.032)
R^2	0.89	0.92	0.89
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Control variables include population, number of EU migrants, and number of non-EU migrants. Attitudes are toward immigrants measured using data from British Election Survey (BES), which are then standardized to have mean 0 and standard deviation 1. All specifications include quarter and CSP fixed effects. Column (2) has fewer observations because two CSPs have singleton observations.

Table A.11: Belief Shock and Hate Crime:
Controlling for GDI

	Dependent Variable: Standardized Hate Crime		
	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)
	Panel A: UKIP Event		
Post-UKIP × Belief Shock	0.041	0.028	0.032
	(0.012)	(0.013)	(0.014)
GDI	0.323	0.364	0.131
	(0.068)	(0.082)	(0.061)
R^2	0.91	0.93	0.90
Observations	17,024	16,912	17,024
	Panel B: BREXIT Event		
Post-Brexit × Belief Shock	0.058	0.059	0.064
	(0.024)	(0.024)	(0.025)
GDI	0.507	0.614	0.403
	(0.139)	(0.147)	(0.105)
R^2	0.90	0.92	0.89
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Belief shock is standardized to have have mean of zero and standard deviation of 1. Control variables include population, number of EU migrants, number of Non-EU migrants. Additional economic variable includes gross disposable household income. This variable is expressed in millions of nominal pounds (£). Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column 2 has fewer observations because two CSPs have singleton observations.

Table A.12: Belief Shock, and Hate Crime:
Controlling for Taxes

	Dependent Variable: Standardized Hate Crime		
	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)
	Panel A: UKIP Event		
Post-UKIP × Belief Shock	0.042	0.030	0.033
	(0.013)	(0.014)	(0.014)
Tax	0.260	0.291	0.114
	(0.062)	(0.073)	(0.049)
R^2	0.91	0.93	0.90
Observations	17,024	16,912	17,024
	Panel B: BREXIT Event		
Post-Brexit × Belief Shock	0.053	0.059	0.064
	(0.025)	(0.025)	(0.026)
Tax	0.333	0.355	0.245
	(0.114)	(0.119)	(0.094)
R^2	0.90	0.92	0.89
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Belief shock is standardized to have have mean of zero and standard deviation of 1. Control variables include population, number of EU migrants, number of Non-EU migrants. Additional economic variable includes current taxes paid on income and wealth. This variable is expressed in millions of nominal pounds (£). Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column 2 has fewer observations because two CSPs have singleton observations.

Table A.13: Belief Shock and Hate Crime:
Controlling for Benefits Received

	Dependent Variable: Standardized Hate Crime		
	Region × Time Trend	Police × Time Trend	Police × Post-Event
	(1)	(2)	(3)
	Panel A: UKIP Event		
Post-UKIP × Belief Shock	0.046	0.030	0.032
	(0.013)	(0.014)	(0.014)
Benefits Received	0.072	0.007	0.006
	(0.057)	(0.074)	(0.054)
R^2	0.91	0.93	0.90
Observations	17,024	16,912	17,024
	Panel B: BREXIT Event		
Post-Brexit × Belief Shock	0.070	0.079	0.072
	(0.027)	(0.028)	(0.028)
Benefits Received	0.013	0.014	-0.032
	(0.092)	(0.110)	(0.075)
R^2	0.89	0.92	0.89
Observations	21,577	21,435	21,577
Number of CSPs	304	302	304
CSP Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
Region × Time Trend	Yes	No	No
Police × Time Trend	No	Yes	No
Police × Post-Event	No	No	Yes

Notes: OLS estimates with robust standard errors clustered by CSP. Belief shock is standardized to have have mean of zero and standard deviation of 1. Control variables include population, number of EU migrants, number of Non-EU migrants. Additional economic variable includes social benefits received. This variable is expressed in millions of nominal pounds (£). Panel A shows results using information shock from the UKIP event. Panel B shows results using information shock from the Brexit event. All specifications incorporate quarter and CSP fixed effects. Panel A covers a sample period from 2002 Q2 to 2016 Q1, whereas results in Panel B covers a sample period from 2002 Q2 to 2019 Q4. The sample size is larger in Panel B because it includes fifteen additional quarters. Column 2 has fewer observations because two CSPs have singleton observations.