Terror and Tourism:

The Economic Consequences of Media Coverage

Timothy Besley, Thiemo Fetzer and Hannes Mueller

(This paper also appears as CAGE Discussion paper 449)

December 2019 No: 1235

Warwick Economics Research Papers

ISSN 2059-4283 (online)

ISSN 0083-7350 (print)

Terror and Tourism:
The Economic Consequences of Media Coverage

Timothy Besley   Thiemo Fetzer   Hannes Mueller*

December 17, 2019

Abstract

This paper studies the economic effects of news-coverage of violent events. To do so, we combine monthly aggregated and anonymized credit card data on tourism spending from 114 origin countries and 5 tourist destinations (Turkey, Egypt, Tunisia, Israel and Morocco) with a large corpus of more than 446 thousand newspaper articles covering news on the 5 destination countries from a subset of 57 tourist origin countries. We document that violent events in a destination are followed by sharp spikes in negative reporting at origin and contractions in tourist activity. Media coverage of violence has a large independent effect on tourist spending beyond what can be accounted for by controlling for the incidence of violence. We develop a model in which tourist beliefs, actual violence and media reporting are modelled together. This model allows us to quantify the effect of violent events and reporting.

*Corresponding author: Mueller, h.mueller.uni@gmail.com. Besley is based at the London School of Economics, Fetzer at Warwick University and Mueller is based at IAE - CSIC. We thank seminar audiences at Paris School of Economics, CAGE/Warwick University, Banco de Espana, CIREQ in Montreal, Barcelona GSE Summer Forum, London School of Economics, CUNEF Madrid. We are grateful to the International Growth Centre (IGC) and to the Mastercard Center for Inclusive Growth for their support. We thank Chris Dann, Olga Starchikova and Bruno Conte Leite for excellent research assistance. All errors are our own.

1 Introduction

Media reporting plays a critical role in spreading information about events of public interest. Violent events are particularly prone to attract intense media coverage. Even single isolated events can therefore erode perceptions of security if they attract intense coverage. This is particularly problematic if reporting deters visitors from abroad, who could contribute to the economy by trading in goods, through spending as tourists or by bringing in foreign capital and expertise. Given the benefits of openness and economic integration in general (see Frankel and Romer, 2008; Melitz and Trefler, 2012) and tourism in particular (see Faber and Gaubert, 2016), media reports could then have detrimental consequences for economic development.

Little is known about the extent to which news coverage shapes the economic impact of violent events. Nor do we know whether the economic repercussions of violent events are short-lived or persistent. Gaining insights into these questions requires appropriate data to measure both, the economic responses to insecurity, and the nature and timing of news coverage. To quantify the effect of news coverage we also need to integrate this data into models of news reporting and beliefs. This paper makes a unique contribution using two novel data sources. First, we use aggregated and anonymized spending data from Mastercard (hereafter "aggregate spending") for one hundred and fourteen origin countries in five destinations (Egypt, Israel, Morocco, Tunisia and Turkey) as a measure of tourist activity.[1] This data offers the advantages of being available monthly and being *dyadic*, i.e. it reflects aggregated spending from an origin country (where the cardholder accounts are registered) and a destination country. Since tourism is an export industry, this is similar to exercises that measure international trade flows at a dyadic level.

Figure 1 shows the correlation of aggregate spending with a specific violent incident in which thirty-nine tourists were killed on June 26th 2015 in Sousse, Tunisia. The majority of the victims were UK citizens. The lines in the figure contrast the response of tourism spending on two specific dyads based on origin country: British (the dotted

[1] Mastercard made the anonymized and aggregated data available subject to robust privacy and data protection controls – and in line with their principles guiding the ethical collection, management and use of data.

line) and German (the dashed line), while overall average spending patterns across all dyads is indicated by the solid line.

(Figure 1)

The figure highlights that aggregate tourism spending falls immediately in the months following the attack. However, tourism spending from Britain dropped much more compared to tourism spending from Germany. One candidate explanation, which we explore here, is that this heterogeneity is down to the differential intensity of news reporting on the event in the two tourist origin countries.

To capture the news environment, the second data set we built is a corpus of nearly half-million news articles. This corpus covers articles from fifty-seven origin countries covering our five destinations from 2009 to 2016. We auto-translate all articles and identify a subset of articles that report on fatal violence or violence against tourists. Given the size of the corpus we use methods from computational linguistics and supervised machine learning to develop an automated classifier of reports on violence. This classifier then gives us a measure of the *relative intensity of reporting* on violence at the dyad which is matched with the data on spending flows.

We use the news data to show that differential media coverage in origin countries can explain the heterogenous effect around violent events suggested in Figure 1. We document a robust relationship between the intensity of reporting on violence and subsequent drops in tourism activity. These results are found even after fully accounting for destination- and origin-specific variation. Moreover, there are no discernible pre-trends in either news reporting or spending. Lastly, we also use an instrumental variable approach leveraging the distribution of nationalities of casualties around known events, yielding very similar results. The effects that we find are sizeable; we estimate that if media-reporting on a specific dyad switches from reporting on topics unrelated to violence to covering only stories about tourists being targeted, then tourism spending drops by about 56 percent a month later. The effect of news reporting that we find comes from the *share of news* coverage dedicated to violence. Furthermore, this effect is persistent, lasting for about nine months following the coverage.

Motivated by these core findings, we fit a statistical model of violence, reporting and spending to the data. Its construction is inspired by the work of Tversky and Kahneman (1974) who propose that potential tourists may think in terms categories such as “safe” and “dangerous”. We assume that tourists try to avoid destinations perceived to be “dangerous” and model this underlying risk as a latent state variable which drives both reporting and violence. In this way we are able to model changes in the objective risk, how this drives reporting and how both together affect tourist spending.

In order to capture the role of news in the model we suppose that some tourists are ”naïve” in the sense that they only observe what is covered in the news. We contrast this type of tourist with a ”sophisticated” type of tourist who observes the objective measures of violence and builds her perception of the risk of danger based on this data.[2] Using a grid-search we estimate the mixture of tourist-types that best captures the observed patterns in aggregate spending in response to violence. Since we model both reporting and risk perceptions together, we can also show explicitly how high levels of reporting of non-violent events can effectively “drown out” reporting about violent events. As a result, naïve tourists in our model might not react at all to news on violence if the overwhelming majority of news is on other issues.

Finally, our model-based approach also gives insights into the pattern of persistence of media-coverage on spending. We hypothesize that booking vacations depends on beliefs held at the booking or cancellation date. We then back out from the data an estimate of what share of tourists appear to have booked or cancelled their travel at each date. This exercise suggests that the pattern of persistence in the spending response is “explained” by more than 40 percent of tourists booking their vacations more than three months in advance implying that there is some persistence in spending to violence and news reporting.

This paper contributes to a large and growing literature which studies the impact of the media on economic and political outcomes (see Strömberg, 2015 and Prat and Strömberg (2011), for reviews).[3] Our contribution is to look at news events and

[2] Both labels are obviously a modeling device as we only observe aggregates disaggregated by month and origin/destination dyad.

[3] The impact of the media on politics and economics has been the subject of many papers: Stromberg

coverage across multiple countries. This complements a body of work that has focused in detail on US news coverage and its consequences. For example, Eisensee and Strömberg (2007), shows that news on droughts affect US disaster relief. Similarly, Durante and Zhuravskaya (2018), suggests that offensives in the Israel Palestine conflict are strategically aligned to minimize news coverage in the US, while Jetter (2017) suggests that Al Qaida activity may be endogenous to preceding US television news coverage.[4] We contribute to this literature by providing dyadic news data which we embed in a model of violence, reporting and beliefs.

The paper relates to a growing literature which uses text as data. Drawing on national newspapers and a simple dictionary, Baker et al. (2016) construct an economic policy uncertainty index for a host of countries. Hassan et al. (2019) make use of computational linguistics methods to develop a dictionary of terms for the measurement of political risk documenting that increased political risk induces more lobbying activity. Mueller and Rauh (2017), following a similar approach to Hansen et al. (2018), use unsupervised learning, so-called topic models, to assess to what extent Western (US and UK-based) media coverage can predict violence risk. In this paper, we instead deploy supervised machine learning methods to produce a measure of violence in the news. This approach allows us to test explicitly, through cross-validation, how good our method is in identifying reporting on violence in the news.[5] The good performance of our method suggests that this way of producing data from text, i.e. letting the machine figure out which parts of the text are most relevant, might also be useful in other applications.

We show that the economic impact of violent events on tourism activity is significantly driven by the underlying news reporting. In this regard our work relates to an emerging literature on how news "shocks" affect economic behavior (see Ramey, 2011). Arezki et al. (2017) documents that news reports on resource discoveries have

(2004) on redistributive spending, Besley and Burgess (2002) on government accountability, Gentzkow (2006); Bursztyn et al. (2017) on voter turnout, Snyder and Strömberg (2010) on citizen knowledge, DellaVigna and Kaplan (2007) on voting patterns, Durante et al. (2019) on the proclivity towards populist rhetoric.

[4]We observe that news coverage sharply responds to violent events, but not in anticipation.

[5]There is still relatively little work in economics leveraging supervised machine learning. We use cross-validation to show that an ensemble of naive bayes and random forests provides relatively large gains over simpler methods commonly used (see Manela and Moreira, 2017; Becker and Pascali, 2019).

near immediate impacts on the current account and Eggers and Fouirnaies (2014) document that news about the technical declaration of a recession has a contractionary effect on the economy. This raises questions about how people collect and process news and whether they might overreact to particular forms of coverage (see Azeredo da Silveira and Woodford, 2019, Handel and Schwartzstein, 2018 and Bordalo et al., 2018). Given that we explain a significant amount of heterogeneity in the response to the same facts driven by news reporting, our findings also support the idea of "overreaction" and/or selectivity in access to information. This relates to discussions beyond economics. For example, Singer and Endreny (1993) suggests that hazards are distorted by mass media and that *"emotion, not reason, is likely to govern our response to those hazards for which we depend on the media for information."* (p.41) This is particularly relevant if social media amplify echo chambers (Mullainathan and Shleifer, 2005; Gentzkow and Shapiro, 2011), which can spread fake news and/or entrench extreme views (Barrera et al., 2017; Allcott and Gentzkow, 2017).

We also contribute to an emerging literature on the consequences of violence and disorder on trade and economic integration. For example, Besley et al. (2015) measure the cost of piracy in the Gulf of Aden on shipping costs and hence on trade. They emphasize that violence can increase trade costs which the trade literature has shown can have a significant impact on trade flows (see, Feyrer, 2019, Donaldson, 2018). However, the mechanism we focus on here is closely related to Burchardi et al. (2019) who show that better information on a country, due to ancestry, is an important driver of foreign investment decisions. Tourism is an increasingly important sector that supports up to 313 million jobs across the globe.[6] We show that tourists with more information react less to idiosyncratic media reporting because they have a broader informational base and this can be an important factor in the overall effect of violence on economic ties. This is particularly relevant in the MENA region which is one of the least economically integrated regions (Rouis and Tabor, 2012) and where growing economic ties to Europe are important.

[6]See WTTC (2018). A small literature within economics studies tourism using robust methods. For example, Faber and Gaubert (2016) show that, in Mexico, tourism produced significant local economic gains. Neumayer (2004) uses cross country panel data to show that violence is negatively associated with tourism arrivals.

There is now a large literature on the economic costs of violence to which this paper contributes. For example, Abadie and Gardeazabal (2003) documents the sizable negative economic consequences of terrorism in Spain and Besley and Mueller (2012) looks at the impact of house prices using regional variations in violence in Northern Ireland. More recently this literature has shifted towards identifying the mechanisms through which lack of security affects the economy. For example, Amodio and Di Maio (2018) shows how firms bear the direct and indirect costs of violence and political instability. Jha and Shayo (2019) explore how individuals re-evaluate the costs of conflict upon being exposed to financial assets whose prices may be vulnerable to the economic risks of conflict. Brodeur (2018) shows that successful terror attacks in the US reduce the number of jobs and total earnings in the affected counties. This paper adds to this literature by highlighting a new mechanism: news coverage itself can amplify the negative economic consequences of terrorism.

The remainder of the paper is organized as follows. In section 2 we discuss the data used in some detail. Here, we also discuss the supervised learning method through which we make the text data usable for the subsequent analysis. In section 3, we present reduced form results of the average effect of violence on tourism activity before incorporating the news data. In section 4, we propose a statistical model and fit this on both the news and the tourism activity data. Concluding comments are in section 5.

2 Data and Feature Extraction

This paper uses three main data sources: (i) aggregated spending data by origin and destination country, (ii) measures of terrorism and conflict and (iii) a large corpus of dyad-specific news content. We describe each of these followed by a discussion of the supervised machine learning method that is used to identify news coverage of fatal violence and attacks on tourists.

2.1 Aggregated Spending Data

Mastercard provided us access to an anonymized and aggregated monthly data set which included the number of transactions and number of active cards based on spending in five different countries (Egypt, Israel, Morocco, Tunisia and Turkey) by the country of origin of the card. Mastercard made the anonymized and aggregated data available subject to robust privacy and data protection controls. Where Mastercard's controls may have resulted in, for example, a blank monthly-dyad observation, we excluded all of those dyads where we have fewer than 60 months (5 years) of data and origin countries with fewer than 3 out of 5 destination dyads.[7] The origin countries in our sample span all continents but trend towards higher income countries and those that are closer to the destination countries.[8] Figure 2 maps all of the origin (card-issuing) countries that we have in the sample.

(Figure 2)

There are dramatic differences between origin countries with low volume of cards active per month in tourism spending, such as countries like Haiti and Namibia compared to higher volume tourism spending from countries such as Germany and the United States.

The aggregated card data can be a proxy for annual patterns in travel flows: for a small set of countries annual data on travel flows is provided to the United Nations World Tourism Organisation (UNWTO). Appendix Figure A1 highlights that the annually-aggregated card data correlates with the travel flows data very closely. Appendix Table A1 presents further regression evidence highlighting the close fit.

2.2 Data on Violent Events

We use five different data sources, three of which are hand-coded event data while the other two are constructed using automation.

Manually-coded data sources As our core data on terrorism we use the Global Terrorism Database (GTD) which is an open-source database that codes information on terrorist events around the world between 1970 and 2017 based on reports from a variety of media sources. These reflect world-wide rather than country-specific news coverage and the information is verified by the GTD research team to establish the

[7] Results are robust to changes in this rule.

[8] We also include cards originating in the destination countries themselves. These data can be dropped leaving results unaffected.

credibility of the information source. The data focus on the type of violent events that are likely to influence the desirability of a destination for tourists.

As supplementary human-coded sources of data, we also leverage the Georeferenced Event Dataset (GED) provided by the Uppsala Conflict Data Program (UCDP).[9]

Automated Data We use the Integrated Crisis Early Warning System (ICEWS) database created for the Defense Advanced Research Projects Agency (DARPA) and Office of Naval Research (ONR). This event-level data comprises coded interactions between socio-political actors (i.e., cooperative or hostile actions between individuals, groups, sectors and nation states). Similar to the approach used in Fetzer (2019), events are identified in a fully automated way and are extracted from news articles, essentially consisting of triplets based on a subject (a source actor), an event type (indicated by a verb) and an object (a target actor). Geographical-temporal metadata are also extracted and associated with the relevant events. In this paper, we focus on events that have been coded as assaults, which include events like hijacking, suicide bombings and assassinations and along with data on fights or escalations, which includes the use of military force, fights with artillery and tanks and aerial bombing.

The second automated dataset is the GDELT platform which monitors the world's news media from nearly every corner of every country in print, broadcast, and web formats, in over 100 languages, every moment of the day stretching back to January 1, 1979 to produce data on events.[10] GDELT is more inclusive, yet it may also include also more false positives and it also has less stable source material over time and codes the news sources only from 2014 onwards.

Both of these data sources have in common that they aim to identify the "true" set objective violent events. Neither of them provides a measure of the likely salience of an event nor the intensity of news coverage about a violent event across different countries.[11] We next describe how we construct a dyadic dataset of news coverage for 57 of our issuing countries, i.e. for 285 dyads.

[9]Results are also similar when studying the Armed Conflict Location & Event Data Project (ACLED) data. As these are currently only available for the three countries on the African continent we do not include them in the analysis.

[10]This data has been used by Manacorda and Tesei (2016).

[11]To the best of our knowledge, such a data set does not exist.

2.3 Data on News

The news data variable that we construct is intended to proxy the news coverage that potential tourists have access to in a given country when they decide on their holiday destination. A key concern here is measurement error both because the media landscapes differ across countries and because it is not clear a priori which specific news items are viewed. To obtain dyad-specific variation in news coverage, we develop a large scale corpus for 57 tourist-origin countries. For each tourist-origin country we identify a leading news source for which a digital archive of all articles is available over our sample period. For each of these sources, we then download all articles that relate to each of our five destination countries covering the period from 2009 to 2016. The tourist origin countries for which we have both card data as well as media coverage data are indicated in dark grey in Figure 2. The countries for which we have news data represent, by far, the biggest chunk of the world economy, comprising all G20 nations along with a host of other significant emerging-market economies. Hence, although we cannot say that this is globally representative, the consequences of changes in tourist spending in these countries are likely to be economically important for the destination countries that we study.

The resulting data set contains more than 450,000 individual articles, out of which 307,000 articles were translated into English using *Google* Translate. The translation to English allows us to produce a single consistent classifier to code individual articles.[12]

2.4 Supervised Machine Learning Approach

We use supervised machine-learning to classify individual articles according to whether they report violent incidents or incidents directly involving tourists. We proceed in four steps. First, we use human coding to classify a subset of the data which we use as a training dataset to generate our news indicators. Second, we use supervised machine learning to train a set of classifiers to predict the human classifications in the training set and classify unseen articles. In this step, the availability of training data allows us to check performance of the classifier using cross-validation. Third,

[12] Appendix Table B1 presents the main source by country, the origin language and the number of articles included in our database. For a few countries only news wire agency reports were available; our results are robust to dropping these countries from the analysis.

we check a subset of the classified articles by hand to generate out-of-sample performance measures and reduce measurement error further. Finally, we aggregate the resulting scores to produce a count of news about violence for each dyad/month or dyad/day. We then express this as a share of all news in the same dyad/month.

Training data set To build the training set, human coders classified a sample of around 30,000 articles (approximately 7% of the data). The coding guidelines consisted of two binary classification questions that were used to construct two separate measures of violence. Specifically, human coders were asked to flag up individual articles with a binary indicator if:

1º *the article indicates that there were fatalities as a result of violence*

2º *the article indicates that tourists were harmed due to a violent event*

The underlying classes are quite unbalanced relative to the population of articles. This can make it difficult for statistical learning methods leveraged for classification purposes to separate the data adequately. To navigate this issue, in drawing our training sample, we follow Japkowicz and Stephen (2002) and oversample articles around days for which the Global Terrorism Database indicated that an event occurred. In addition, when training our classifier we sample such that we get a 1:1 set.

Classification approach In the second step, we train a set of classifiers in Python using the scikit-learn packages developed by Pedregosa et al. (2011). Individual articles are represented using the common bag of words language model so that each document can be expressed as a vector of counts. We use standard stemming procedures and remove stop words. We then produce all trigram word features and exclude terms that appear in less than 100 documents.

We use an ensemble of three classifiers to identify violence. To build the ensemble we made extensive use of cross-validation with our training data to get an impression of the likely out-of-sample performance and to refine what part of the text to focus on, which classifiers to use and how to combine them. All three classifiers are built by looking at the full text and headline. We use a simple Naïve Bayes classifier and two Random Forest classifiers with hyperparameters described in the Appendix D.

This produces 3 different classifiers, indexed by k, which allow us to obtain for each document, denoted by D_i, three estimates of the probability that classifier k contains news coverage of the type that interests us, denoted by $\hat{P}_k(Y_i = 1|D_i)$, where Y_i is an indicator denoting whether a given document D_i is either covering violent events with fatalities or violent events in which tourists were targeted.

Naïve Bayes methods belong to the class of generative linear classifiers, is known to perform well with textual data and sparse feature sets. Random Forests, on the other hand, are particularly suitable to allow for non-linearities using smaller feature sets. The only difference between our two Random Forests, is that in one of them we first use Singular Value Decomposition (also referred to as Latent Semantic Analysis which has recently been used in Iaria et al. (2018)) to reduce the dimensionality of the feature space from (tens of) thousand of word counts features into a much lower 100-dimensional continuous score representation of individual documents D_i. These individual components are then used as numeric features in the construction of the classification trees using the random forest formulation.

In cross validation on three folds our ensemble reaches an AUC of 0.95 and an average precision of 0.85 for fatal violence and an AUC of 0.97 and average precision of 0.65 for attacks on tourists. These are very good statistics but they come from an evaluation of a balanced dataset and precision falls when we instead evaluate an imbalanced sample. This is an important issue for spotting of violence against tourists as this is a heavily imbalanced class even in the training data.

Classification Ensemble and Validation For classification purposes, we use a soft voting ensemble method, i.e. we average our three different classification scores $\hat{P}_k(Y_i = 1|D_i)$ according to the function:

$$1(D_i) = \begin{cases} 1 & \text{if } [\frac{1}{3}\sum_{k=1}^{3} \ \hat{P}_k(Y_i = 1 \ |D_i)] > c \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

To chose the cutoff c in (1), we count how often the indicator, $1(D_i)$ would have been correct for different values of c within the training sample. The best for accuracy would be to pick a cut-off of $c = 0.5$. But we know from cross-validation that precision suffers due to the imbalanced sample. We are concerned that we get too many false positives and becomes meaningless. We therefore choose a higher cutoff which provides 90 percent precision within our training sample.[13] This cutoff gives us 16,906 news articles with fatal violence and 1,082 news with violence against tourists out of over 450,000 articles.

To reduce measurement error we conducted some ex-post manual coding for the classification of articles indicating violence against tourists. While our results are robust to relying only on the machine-generated output, it is prudent to perform such a manual check and some amount of ex-post refinement. We considered all articles with an ensemble probability indicating violence against tourists above 0.75 along with the top 100 articles ranked by the ensemble estimate from in (1) all origin sources.[14] We set $1(D_i) = 0$ by hand if we find false positive and set $1(D_i) = 1$ if we find false negatives. Of $1,082$ observations that were marked positive by the algorithm we recoded 103 to negatives, implying that our method did indeed achieve a precision of over 90 percent out-of-sample. In the almost 5,000 additional news items that were hand-coded we only found an additional 608 positives with a rapidly declining rate so that we suspect that the remaining articles will not contain a lot of actual positives. After hand-coding we therefore have $1,587$ positives in over $450,000$ negatives that feed into our media coverage-based measures of violence against tourists.

In the Online Appendix D we describe the classification approach in greater detail, while appendix Tables B2 and B3 provide some sample headlines of articles coded as covering violence and flagged up as capturing that tourists are targeted by a violent event. In the appendix we also discuss the "mistakes" made by the algorithm and why they are often capturing something indicating risks to tourists. It is therefore no surprise that our results, even in the most demanding specifications, are robust to using only the raw $1(D_i)$ that come out of our automated procedure and using different cutoffs.

This is also important from a methodological perspective. We have managed to

[13] Our results are robust to using alternative cut-offs. In Appendix Table A6 we use both a higher cut-off with 95 percent precision and the Bayes-optimal cut-off of 0.5.

[14] We do the latter to ensure that the model has not only fit to sources that emit a lot of news like news agencies in Russia and China.

provide a meaningful, fully-automated way to identify fatal violence and violence against tourists even though they only appear in about 4 and 0.4 percent of all articles, i.e. are extremely rare. We did this simply by asking our research assistants to code a subset of the articles - the classifier then automatically extracted the relevant features from the data. Furthermore, our supervised learning approach allowed us to check the error rate explicitly and to reduce it through setting hyperparameters and building of the ensemble. This would not have been possible with an unsupervised or dictionary-based method.

2.5 Patterns in the Reporting Data

Before turning to the full analysis, we document how the news reporting relates to underlying events beginning with daily data. This provides evidence in support of the underlying common trends assumption which matters in the empirical analysis below where we require that reporting only occurs *after* an attack and not prior to one.

Daily Data To look at patterns of news reporting around known events, we use the GTD daily event data to construct a balanced panel at the dyad level covering two week windows around each event. In total there are 3704 recorded events across the five destinations. Given the 57 countries for which we have media coverage, the balanced daily event-level dataset comprises 6.1 million rows.

This data layout allows us to explore the pattern of news reporting around known events. One concern, following Jetter (2017)'s study of US media coverage, is that news stories might precede (and even encourage) acts of violence within a time window (such as a week). This would show up in our data as increases in reporting intensity *before* GTD events. To investigate this possibility, we estimate the following empirical model:

$$p_{hdt} = \alpha_k + \alpha_{hd} + \alpha_t + \sum_{\tau=-14}^{14} (\beta_\tau \times \text{Timetoevent}_{e,t-\tau}) + \epsilon_{hdt}$$

where e indexes a specific event, h and d indicate the reporting dyad, while t indicates time which is now a daily observation. The above regression controls for event fixed effects, α_k, dyad fixed effects, α_{hd}, and daily fixed effects, α_t. In the case of multiple events in close temporal proximity, we would be double counting the reporting on dyad $\{h, d\}$, and hence we adjust standard errors to allow for two-way clustering at the level of the dyad and the event.

(Figure 3)

In Figure 3 we plot the point estimates $\hat{\beta}_\tau$, which suggests that there is no anticipatory element in the reporting data. Panels A and B show the measures generated from our method for classifying articles. Specifically, we construct the share of articles per day that are classified as reporting either fatal violence or tourists being attacked. The patterns suggest a sharp increase in the share right after the event date. This dissipates quite quickly with most reporting occurring on the day of the event and for around two days afterwards. It is important to note that this happens despite the fact that the total number of news stories increases slightly, i.e. we find this relative reporting effect despite increased reporting overall.[15]

Monthly Aggregates In our analysis we use aggregates of our news measures to the monthly level. Figure 4 reports the mean shares at a monthly frequency for the four countries most affected by violence against tourists in our sample period (Tunisia, Turkey, Israel and Egypt). It depicts the average share across all dyads of monthly events defined by (1) for violence against tourists – the red dashed line with the axis on the right hand side – and (1) for fatal violence on a monthly basis – the blue solid line with the axis on the left hand side.

(Figure 4)

Figure 4 shows a lot of variation across time in reporting for all countries. But there is also considerable variation in the intensity of reporting across destinations. Reporting on violence is often a considerable part of reporting on Tunisia. At the time of the Sousse attack, for example, violence against tourists occupied around 40 percent of all news. Reporting in Egypt, Turkey and Israel is more intense for fatal violence than it is for violence against tourists. However, this coverage never occupies

[15] In Appendix A.1 we provide some further evidence shedding light on which event characteristics are associated with, on average, more extensive media coverage.

more than 10 percent of the news. The most extreme example is Israel where news on violence never exceeds 7 percent of reporting and violence against tourists never more than 3 percent.

3 Reduced-form Evidence

In this section, we present reduced-form evidence on the relationship between spending and violence. We begin with country-level violence and then present the findings with dyad-specific news coverage. Both sets of results show that there is a highly robust relationship between aggregated spending and violence which depends not only on violent events but how intensively they are covered by news media.

3.1 Country-level Violence

We begin by looking at the relationship between the (log of) spending by origin country h in destination country d at date t, denoted by y_{hdt}, and violent events using the following specification:

$$y_{hdt} = \alpha_{hd} + \alpha_{ht} + \alpha_{dm(t)} + \xi v_{hd,t-1} + \varepsilon_{hdt} \tag{2}$$

where α_{hd} are dyad fixed effects, α_{ht} are origin country/time fixed effects and $\alpha_{dm(t)}$ are destination/month of year fixed effects. The inclusion of origin country-time fixed effects capture a range of seasonal, political and economic effects in the origin country and the destination/month fixed effects capture seasonal patterns in spending in the different destinations. The first set of fixed effects implies that we are effectively looking at the rate of tourism spending from origin countries in the five different destinations. Any fluctuation in the overall flow of spending into the region will be absorbed by the home country/time fixed effect. In addition to aggregated spending as an outcome variable, we will also consider the number of active cards on which spending is happening as an outcome measure.

Our core violence measure, denoted by $v_{hc,t-1}$, is lagged by one month to capture the possibility that tourism reacts to past violence. We expect to find that $\xi < 0$ in (2), i.e. violence deters spending. We use four sources of data on violent events at the country level in different versions of (2). In order to make the magnitudes from different data sources comparable, we divide the right-hand-side variable measuring violence by its respective standard deviation.

Table 2 reports regressions from the specification in (2) and shows compelling evidence of a negative link between violence and card spending. Columns (1) through (4) show that there is a significant correlation between all five measures of violence and the level of tourism spending in a country. The size of the coefficients is in the range of 4% to 7.6% decrease in spending for an increase of violence by one standard deviation.

In Column (5) we try to get a more complete impression of the relationship between violence and spending using all available information from the different measures by combining nine different measures using a principal component analysis. We then represent $v_{hd,t-1}$ in (2) with a four dimensional vector comprising the first four principal components, with the results reported in column (5). In line with the results in columns (1) through (4), we find a robust negative relationship between principal components 1, 2 and 4 and spending. In terms of magnitude, spending falls by about 7% with an increase in the first component and by about 4% with the second component. Since this summarizes information from a range of sources, we will use this representation of violence in the analysis that follows.

Columns (6) - (10) show that we obtain similar results when using the log value of number of active cards as the dependent variable. This is important as it indicates that the main spending effect is coming from the *extensive* margin, i.e. the usage of cards from origin countries in the destination countries rather than the average amount spent per card.

(Table 2)

Together these results are consistent with the idea that violence may deter potential tourists. Moreover, this is true even when we include, dyad, home country $\times$ time and month effects in the specifications so that the effect of violence is relative to mean dyad spending in a given month. The results are therefore not influenced by macro-trends in the origin country (country in which the cards are issued).

To allay the concern that results based on (2) could be explained by different time trends between times/places which experience violence and those that do not, we conducted an event-study which studies patterns in aggregated spending and the number of active cards around known violent events. It is comforting to see in Appendix Figure A4 that there is no evidence of any anticipatory contraction of spending or reduction in the number of active cards prior to an event taking place. On the contrary, we observe sharp contractions in card spending and the number of active cards with a one month delay only *after* a violent GTD event occurs.

3.2 Exploiting Dyadic Variation in News Coverage

We now shift focus away from the violence data in an attempt to understand whether there is a differential effect of media reporting about violence on tourist activity. This allows us to explore dyad-specific responses to violence as mediated via news coverage.

Core results The core specification in this section extends (2) to:

$$y_{hdt} = \alpha_{hd} + \alpha_{ht} + \alpha_{dm(t)} + \xi_1 n_{hdt-1} + \xi_2 v_{hct-1} + \varepsilon_{hct} \tag{3}$$

where, as above, our independent variable is the (log of) tourism spending. In this instance, we measure v_{hct-1} using the first four principal components of violence across the seven violence measures used in the previous section; these capture more than 90 percent of the variation in the country-level violence variables. The variable n_{hdt-1} is our dyad-specific news variable.

In some specifications we will use α_{dt} instead of $\alpha_{dm(t)}$, i.e. we include destination $\times$ time fixed effects. These fixed effects capture *all* variation at the destination/time level including news events which are reported on with a common level of intensity across origin countries. The relationship between news coverage and spending is then identified through idiosyncratic variation in the intensity of news reporting across origins.

Define $B_{hdt} = \sum_{i \in hdt} 1(D_i)$ as the monthly *count* of negative news stories in dyad $(h.d)$ at date t, either about fatal violence or attacks on tourists, based on equation (1). Then our core variable to represent news coverage in a dyad is

$$n_{hdt-1} = \frac{B_{hdt-1}}{N_{hdt-1}} \tag{4}$$

where N_{hdt-1} is the count of *all* news stories featuring country d reported in our news source for country h at date $t-1$. Thus the variable in equation (4) reflects the news coverage of violence as a *share* of all news. This captures the idea that news coverage of violence affects tourists more when they are important relative to other news. Thus, if bad news stories are swamped by other stories, they will have less impact on tourism spending. We confirm this in section 3.2.

Before presenting the results, it is worth stressing that our analysis is only exploiting within-dyad variation which absorbs all factors like distance or cultural factors. In addition, we are including home country by time fixed effects, α_{ht}, de facto absorbing a host of factors that may drive the level of tourism activity that is explained by origin-country level idiosyncrasies (such as holiday periods, which may differ across countries). In this way we are modelling the rate of tourism activity for a given destination among our sample of five countries *relative to* the overall amount of tourism originating in country h. Hence all magnitudes are based on comparing the attractiveness of our destinations compared to the other five destinations in our data rather than other parts of the world. Thus, we are only able to say whether tourism to Turkey decreased after the terror attacks in the country relative to Egypt, Israel, Tunisia and Morocco. Arguably this is a conservative approach, since there could be reputational externalities whereby tourists shy away from the entire region due to the turmoil in one of our countries.

The results from estimating (3) are in Table 3 where the top panel (Panel A) is based on news coverage of violence against tourists while the bottom panel (Panel B) is for reporting on fatal violence in general. In columns (1) through (3) the independent variable is the (log of) card spending. Column (1) of Panel (A) shows that if the share of stories about tourist violence were to go from zero to one then tourism spending would fall by 0.552 log points or 42 percentage points. This results holds up in column (2) when we add the controls for violent events and the coefficient stays roughly similar. Hence, news coverage is clearly containing valuable information over and above that in the underlying violent events themselves.

Column (3) in Table 3 is our most demanding specification in which we control for destination $\times$ time fixed effects. This set of fixed effects is collinear with any time varying factors at the destination level, such as macro-economic developments or violence at the destination. As a result, in this specification we rely only on the differential intensity in news reporting across different reporting countries. The coefficient on the share of bad news (based on tourist violence) remains highly significant although the coefficient in this saturated specification falls to 0.205 log points. This continues to suggest that a significant part of the overall effect in columns (1) and (2) is driven by pure news reporting. Note, that this also provides some evidence for the idea that tourists are not perfectly informed as the same basic risks at a given destination trigger dramatically different responses depending on the news environment, something which we return to below.

Columns (4) through (6) in panel A of Table 3 repeat the specifications in the first three columns but with the log of active cards as the dependent variable. The estimates are similar which is important as it indicates that the results on spending are not only due to changes at the intensive margin in which tourism spend is less, but rather on the extensive margin as fewer tourists travel to a country following media-coverage of violent events.

Panel B of Table 3 repeats the specifications in Panel A except for measuring reporting on all fatal violence rather than just attacks against tourists. The coefficients are only slightly smaller compared to those presented in panel A. We also find statistically and economically significant relationships throughout although we lose statistical significance in the most saturated specification in column (6). The results suggest that differential intensities in media coverage of violence may have an important independent direct effect on tourism travel and spending, which is particularly relevant given that violence more broadly, not necessarily directed at tourists, is a lot more common.[16]

(Table 3)

Taken together, the results in Table 3 suggest that the media have the capacity to influence tourism spending. The fact that news reporting has a negative correlation

[16] A horse race combining both of these measures together suggests that we find negative and statistically as well as economically significant coefficients for both news measures, suggesting that our news measures are not simply picking up the same type of news. These results are available upon request.

with tourism spending, even when controlling for an array of fixed effects and more objective measures of violence, shows that specific reporting matters over and above the violence itself. That said, it is hard to quantify the relative importance of violence and news from the reduced form analysis. In section 4 we therefore provide a model of tourist perceptions, news and violence which allows us to distinguish the news effect much more carefully from the effect of violence.

Further Results This section provides additional results which lend further support for the idea that intense reporting on violence can impact tourism spending. We also address concerns about reverse causality by using the composition of victims by nationality as an instrument for the intensity of news coverage.

News Coverage Intensity So far, we have assumed that the effect of bad news, B_{hdt-1}, on tourism is weaker when a lot of other news about a country appear at the same time, i.e. that relative frequency $\frac{B_{hdt-1}}{N_{hdt-1}}$ is the right measure to use. One reason to do this is to lower measurement error given the large variation of N_{hdt-1} in the sources we have in our data. But it will also play a crucial role in the theory-based approach that we propose in section 4.

Table 4 presents a range of specifications testing for relative news effects. In Panel A we analyze news reporting on violence against tourists. We first explore the difference between using the count and the share of news coverage by including both in equation (3). The coefficient on the relative measure essentially unchanged compared to column (2) of Table 3. We get an additional effect from the number of bad news, B_{hdt-1}, but this it is small in size - bad news items lower spending by 0.7 percentage points the following month. In column (2) we control for violent events using the four principal violence components.

In columns (3) and (4) we explore how violence intensity matters by constructing a dummy variable for whether news reporting is in different quartiles of the distribution of dyad/months with $B_{hdt-1} > 0$. We find a striking pattern in which spending falls continuously with increasing relative reporting intensity. This is direct support for the idea that it is reporting intensity as captured by $\frac{B_{hdt-1}}{N_{hdt-1}}$ that impacts the tourism spending response. The top quartile experiences a drop of tourism spending of over 25 percentage points whereas the lowest quarter essentially shows no effect.

In Panel B of Table 4 we find the same pattern of coefficients for news reporting on fatal violence. Here, only the relative intensity measures reduces spending and spending falls with higher quartiles. The coefficients are also lower with an 11 percentage point drop in the top quartile where there are now a lot more dyad/month observations. The overall damage of these news stories on spending remains economically important.

(Table 4)

Timing Remember that reporting on violence focuses on very recent events. To capture the dynamic effects of news we can therefore use simple lags and forwards on our main variable, n_{hdt-1}. We show such an analysis in Figure 5. Panel A shows that the coefficients on leads and lags on the tourism news count and Panel B shows the coefficients on leads and lags of the fatal stories news count.

Figure 5 suggests that there is a strong negative effect which starts with the news story and intensifies in the first few months afterwards.[17] In addition, we don't see significant effects on spending leading up to violent events inspite of the fact that such events do tend to be serially correlated. In Panel B we observe that lagged effects persist for some time and that spending does not appear to recover fully. This is consistent with long term effects of violence that have been remarked upon in the macroeconomic literature (Mueller, 2012).

(Figure 5)

These patterns suggest that either perceptions are extremely sticky or that cancellation and search costs imply that tourists who perceived a country as dangerous when booking their holiday are unlikely to switch back to that destination even when the situation has calmed down. To get a more quantifiable sense of the lagged effects of news reporting we model the share of tourists that take a decision regarding their holiday destination explicitly in section 4.

[17]Note, however, that we often have different important events following one after another so not too much weight should be put on these coefficients.

An IV Approach One possible concern is that there are common forces driving reporting and tourism spending if, as terrorists strategically consider their targets to give them maximum media exposure. Another concern is also measurement error since we proxy the news landscape at origin by only one or (at most) two newspaper sources.

We now propose a way of addressing this via an IV approach which uses the nationalities of victims of violence as an instrument. The idea is that demand for reporting on an event increases dramatically if those who are exposed to news stories empathize more with the victims. This may lead to more intensive reporting in the country of origin of the victims and in countries which are "similar" to the origin country of the victims e.g. share a common language or are in the same region.[18]

For a subset of events, we were able to identify the nationality of the individuals killed. If we assume that the distribution of casualties by nationality is random *conditional* on an attack occurring and our fixed effects, then we can use the composition of casualties by country as an instrument for news coverage on a specific dyad. The Sousse attack serves as motivating evidence as shown in Figure 1, since it is notable that while the bulk of casualties was British, 24 of reported fatalities were non-British.

For each attack where we have relevant data, we construct a variable, z_{hdt} to denote the nationalities of the casualties. To amplify power we also construct a version of the measure that attributes casualties from nations to their contiguous neighbors or to countries that share a common language. We then run a first stage regression to explain news reporting on a dyad with the structure of casualties

$$n_{hdt-1} = \alpha_{hd} + \alpha_{ht} + \alpha_{dt} + v z_{hdt-1} + \zeta_{hct}. \tag{5}$$

In Table 5 we present the results from the IV regression using our violence against tourists based news measure in columns (1) - (3) and the general news measure indicating violence with fatalities in columns (4)-(6). Panel A reports the first stage regression based on equation (5) while Panels B and C report second-stage IV regres-

[18]This is not a new idea. Adams (1986) already observed the dramatic differences in reporting depending on the nationality of the victims. Singer and Endreny (1993) contrast, for example, reporting in the US on the heart defect of an american infant compared to reporting on a famine in Ethiopia.

sions with either the log of spending or the log of active cards as the independent variables.

(Table 5)

In column (1) of Panel A we confirm the idea that having a causality from the country in question significantly predicts news coverage in a dyad. Column (2), also counts casualties for contiguous countries, the region of origin (e.g. West Europe, Northern Europe, etc.) and whether they are from a country speaking the same main language. Thus, for example, a British victim may also influence potential tourism in Ireland. We see that these are also strongly significant in predicting news coverage and the F-test on the instruments is, not surprisingly, much larger. Column (3) shows that an instrumentation based solely on the indirect exposure, i.e. contiguity, or sharing the same language together predict news coverage in a dyad quite well.[19]

In Panel B, we show that using the IV approach, there is a robust and negatively significant effect of the share of news stories on the log of card spending. In all cases, we include violence controls, origin/time and destination/month fixed effects. In all cases we find negative coefficients which are much larger than for the OLS. This could be explained by attenuation bias and/or by interpreting the coefficient as a LATE effect where our instrument is picking up something particular about events with identifiable casualties. There are arguments for both. First, we have some dyads for which we have no or little reporting and the news landscape at the origin might indeed look different than what we capture. Second, the coefficients increase much more in size for fatal violence which makes sense as we are now indirectly imposing fatal violence which affected foreigners, i.e. the LATE effect is driven by terrorism instead of military operations. Panel C shows that these results become even more robust when we look at the (log of) active cards as the independent variable.

Taken together, these results increase our confidence in our interpretation of the results as indicative of a causal effect of news coverage in tourist perceptions that depends on origin-specific reporting of violence. And it makes sense that idiosyn-

[19] This approach is similar to Persson and Tabellini (2009) and Acemoglu et al. (2019) who instrument for democracy using democracy in neighbouring countries.

cratic differences in reporting in dyads represent more than variation in objective risk factors faced by tourists.

Robustness In Panels A and B of Appendix Figure A5 we show that our results for violence against tourists are broadly carried by all the different destination countries we study. However, there does appear to be a larger effect for Tunisia, which saw much more violence targeted at tourists.[20] In columns (1) - (4) of Appendix Table A6 we highlight that the results are robust to controlling for dyad-specific linear trends, in addition to destination specific non-linear time trends. We can also control for time-varying exchange rate movements at the dyad level, some of which may be triggered by changes in tourism-based revenues, and find that results are broadly the same. We further show that the results are robust to using alternative cutoffs for the classification of individual articles in the news corpus for which we did not deploy hand-coding. Results are in columns (5) - (8) and are robust except for the lax cutoff with destination time fixed effects. They are also robust to using our cutoff with 90 percent precision without hand-coding. This highlights that using the output of the machine learning method we deploy even without the hand-coding refinement would have led to very similar results.

4 Quantifying the Economic Impact of News Coverage

In this section we provide quantitative estimates of the impact of violent news coverage on tourism spending based on a model of belief formation. We first present a statistical model of violence, news reporting and tourism spending which we fit to the aggregated spending data. After estimating the parameters of the model, we simulate a news "shock" under different conditions and separate the effect of violence from media reporting about the violence. We also show that the model can do a better job than the reduced-form approach at capturing the timing and magnitude of expenditure fluctuations.

It is intuitively obvious that having stories about fatalities or targeting of tourists is unlikely to be positive for potential visitors who are considering visiting a destination.

[20] In Figure A5 we do not include the event-controls. Once these are included, Turkey does not show an additional media effect which indicates that reporting on Turkey had relatively fewer outliers but happened more proportional to violent events.

And the reduced-form results confirm this intuition. But it is not the violence per se that matters since that is already in the past when tourism spending is affected. Violence could matter for two main reasons. First, it could negatively influence beliefs about the general character of a holiday or business destination if violence is treated as a signal about an underlying state. Second, it could be that tourists book their travel in advance so that beliefs in the past affect spending today. In general, the causal chain that this suggests is from acts of violence to changes in beliefs and hence in behavior.

To form beliefs tourists have to get their information from somewhere. Some may trawl a range of sources close to what those who assemble data bases like researchers who compile GTD or GDELT do. But others may simply rely on domestic news sources of the kind that that we have leveraged to get our dyad-specific news coverage measure. A priori we do not know what the mix of such behaviors is likely to be and the reduced-form results tell us little about this. This section therefore develops a model that aims to combine violent events, reporting, tourist beliefs and tourism activity. The key assumption that allows us to tie these three together is that both reporting and violence are representations of a latent state. This allows us to derive a more objective measure of the relative importance of the effect of events vis-a-vis the news reporting on these events on tourism activity.

In our model potential tourists form beliefs before deciding where and when to travel. Whether tourists observe the violent events directly or rely on news reporting will lead to different estimates of the probability that a destination is safe. We will allow a weighted average of these two estimates to predict the tourism spending data and estimate the weight that best fits the data.

The model of belief formation also allows us to estimate weights on how past beliefs affect contemporaneous tourist activity. The focus on past beliefs is motivated by the mechanics of how tourists make their travel arrangements, which typically imply a non-negligible delay between the booking date and the beliefs held at that time and the actual travel date, from which point onwards tourism spending is reflected in the aggregated spending data. We allow for a lagged effect of up to nine months and estimate the weights on these lags that best fit the data. The results show that a structured model of beliefs based on Bayesian updating with these features does a good job at capturing the pattern of changes in tourism spending in response to news and violence.

The model has some features that are standard, i.e. using core features of Bayesian updating. However, we use two non-standard ingredients motivated by the psychology literature: categorical thinking and biases in information sources.

We posit that individuals are categorical thinkers, trying to evaluate whether a given destination is safe or dangerous and form beliefs about the probability that this is the case. There is a wealth of evidence from psychology that people crave such crude categories when making sense of the world.[21] This is one among a range of heuristics and biases highlighted in Tversky and Kahneman (1974).[22] We therefore posit that potential tourists classify countries as either safe or dangerous, forming a judgment about the probability that a country is safe or dangerous for tourists.

There are many different sources of information that a potential tourist could use to research the safety of a holiday destination. Relying only on news reporting in the respective home countries is likely to give only a partial picture, albeit one that can be learned at low cost. However, many individuals may lack the capacity or desire to collect and use all available information and simply take news coverage in their home country at face value.[23]This can produce biased beliefs about the actual safety of danger of a destination since as we have seen, the same event is reported with different degrees of intensity in different countries.

To operationalize this, we suppose that there are two categories (safe and dangerous) and two kinds of tourists (naïve and sophisticated). The latter look at the underlying data on violent incidents and use this to update their beliefs while naïve tourists rely solely on destination-specific news coverage from their home country. This allows us to model the reaction to news and reporting in a uniform framework in which reporting is modelled as providing useful but imperfect signals about the

[21]Fiske (1998) provides a review of social psychology literature; Fryer and Jackson (2008) provide a model based on this idea and a discussion of the biases that this induces in decision-making.

[22]Bordalo et al. (2016) provides a nice overview of different approaches.

[23]Handel and Schwartzstein (2018) provide an overview of the literature. A large literature in psychology focuses on so-called availability heuristics, the tendency to judge probabilities by the ease with which the information can be recalled Tversky and Kahneman (1973).

underlying categorical state.[24]

4.1 The Model

Core Features Suppose that destination country d at date t is characterized by a state, s_{dt} where $s_{dt} = 1$ denotes a *dangerous* destination and $s_{dt} = 0$ denotes a *safe* destination. At each date t, $\hat{P}_{hdt}$ is the belief that a destination country d is dangerous as perceived by potential tourists in country h. Due to different dates at which people book their travel spending is determined by a weighted average of past beliefs. Hence we suppose that equation (3) is replaced by:

$$y_{hdt} = \alpha_{hd} + \alpha_{ht} + \alpha_{dm} + \xi \sum_{\tau=-1}^{-9} \omega_\tau \hat{P}_{hdt+\tau} + \varepsilon_{hct} \tag{6}$$

where ω_τ is the weight on each lagged value, i.e. at date τ. Equation (6) also has the same fixed effects as equation (3). In this framework, n_{dht} and v_{ht} affect spending through affecting beliefs $\hat{P}_{hdt}$. Since we do not directly observe beliefs, we develop a theory-based approach which posits that

$$\hat{P}_{hdt} = \Gamma\left(\Psi_{hdt}, \Omega_{dt}\right)$$

for some function $\Gamma(\cdot)$ where Ψ_{hdt} is the history of news reporting up to date t and Ω_{dt} is the history of violent events up to date t. Note, that only Ψ_{hdt} varies at the dyad level.

Sophisticated Tourists Tourists that we label as "sophisticated" are assumed to read multiple data sources or browse an array of relevant web sites to gather their information. Since this information is not confined to being resident in any specific country of origin, we suppose that such potential tourists have common beliefs. We therefore suppose that they estimate the probability that a country is safe or dangerous by observing Ω_{dt}.

The empirical model that we use for this is based on Besley and Mueller (2012) and Besley et al. (2015) who suppose that the underlying state can be modeled as a Markov

[24] We do not allow for individuals to control their fear (see Becker and Rubinstein, 2011). Yet, it is entirely plausible, even likely, that differences in reporting intensity capture some of this effect.

process which switches between being dangerous and safe. Assume that our measure of violent events is distributed normally i.e., $v_{dt} \sim N(\mu_{sd}, \sigma^2_{sd})$. This allows the mean, μ_{sd}, and the variance, σ^2_{sd} to vary with the state s_{dt}. At each date, there can be a transition between states where p_d is the probability of transitioning from dangerous to safe and q_d is the probability of transitioning form safe to dangerous. This gives a parameter vector for the model with six elements for each destination country d, summarized as $\theta_d = \left\{\mu_{0d}, \sigma^2_{0d}, \mu_{1d}, \sigma^2_{1d}, p_d, q_d\right\}$. This vector can be estimated from the data on violent incidents using an EM algorithm (see Hamilton, 1990) which is now implemented in STATA .

The belief of the sophisticated tourists that a destination is dangerous at time t is then given by

$$\Pi_{dt} = \Pr(s_{dt} = 1 \mid \Omega_{dt}, \hat{\theta}_d), \tag{7}$$

which is based on the estimated parameter vector $\hat{\theta}_d$ and violence history available in t, Ω_{dt}. This belief is updated using Bayes rule as information is revealed, i.e.

$$\Pi_{dt} = \frac{E_{t-1}\left[\Pi_{dt}\right]}{E_{t-1}\left[\Pi_{dt}\right] + \left[1 - E_{t-1}\left[\Pi_{dt}\right]\right] \gamma\left(v_{dt}\right)}$$

where $\gamma\left(v_{dt}\right) = \frac{\phi(v_{dt}|0)}{\phi(v_{dt}|1)}$ is the likelihood ratio derived from the normal distribution densities and where

$$E_{t-1}\left[\Pi_{dt}\right] = \Pi_{dt-1} * p_d + (1 - \Pi_{dt-1}) * (1 - q_d)$$

is the prior from the previous period. For v_{dt}, we use the principal components across the data from different violence sources.[25] Together these make up the elements of the history Ω_{dt}. However, as with any Bayesian approach, the prior history is fully captured by beliefs up to $t-1$. Estimates of $\hat{\theta}_d$ which go into constructing (7) are reported in Appendix Table A7. They show strong persistence in the state in all five destination countries.

Figure 6 gives the estimates of Π_{dt} for Egypt, Tunisia, Turkey and Israel. This approach permits a classification of whether a country is deemed to be dangerous or

[25] To aggregate the different components into one number, v_{dt}, we use the point estimates on the first two components from Table 2.

safe based on the level of violence but in a country-specific manner. Thus, unlike equation (2), the effect of a given change in v_{dt} is heterogeneous across different destinations depending the history and persistence of violence. This makes sense; what would be deemed to be violence pointing to a state of danger in, say, Israel (bottom right) is different from what would be considered danger in Tunisia (top right). These differences show up in the estimates of μ_{sd}. The probabilities based on equation (7) indicate that Tunisia was the first of our destinations to become dangerous based on the level of violence and this was followed by Egypt and Turkey. Danger in Israel based on this method is less persistent.[26] Crucially, objective risk estimates, as displayed in Figure 6 show dramatic differences to the news coverage we displayed in Figure 4.

(Figure 6)

Naïve Tourists To obtain the observed dyadic heterogeneity from our model, we postulate that there are "naïve" tourists who use only information based on news coverage in their own country, i.e. Ψ_{hdt}. We suppose that they base their judgements on news coverage about violence against tourists *in their home country*. To model their beliefs let the state s be associated with a fraction of news stories reporting violence of η_s and the distribution of B_{hdt} and N_{hdt} follows a negative binomial distribution based on this share given by:[27]

$$f\left(B_{hdt}, N_{hdt} \mid s\right) = \begin{pmatrix} N_{hdt} \\ B_{hdt} \end{pmatrix} \left(\eta_s\right)^{B_{hdt}} \left(1-\eta_s\right)^{\left(N_{hdt}-B_{hdt}\right)}. \tag{8}$$

To obtain an estimate of η_s from the data we use our estimate of Π_{dt} and the news data. Specifically

$$\hat{\eta}_s = \frac{\sum_{hdt} \Pi_{dt} \left[\frac{B_{hdt}}{N_{hdt}}\right]}{\sum_{hdt} \Pi_{dt}},$$

[26]The model fits less well for Morocco since the differences in μ_{sd} are minimal between what the model picks as the two categorical states.

[27]We use the negative binomial distribution to capture the fact that news reporting has extremely fat tails. The distribution could be justified by a stopping rule for media consumption but we follow it purely for pragmatic reasons.

where summation is over all dyads and time periods. In effect, this is a weighted sum of the news share variable used in the reduced-form approach with dyad specific variation. Note, that we therefore assume that naive tourists do not know what Π_{dt} is in each period but they know that newspapers will tend to report differently in dangerous situations. The further $\hat{\eta}_1$ is from $\hat{\eta}_0$ the more can naive tourists learn from the news. We find that $\hat{\eta}_1 = 0.022$ and $\hat{\eta}_0 = 0.002$, i.e. tourists can learn something regarding the underlying state by observing that more than about 1 percent of news is bad news.

Naïve tourists then use the likelihood ratio based only on news:

$$\lambda\left(B_{hdt}, N_{hdt}\right) = \frac{f(B_{hdt}, N_{hdt}|0)}{f(B_{hdt}, N_{hdt}|1)} \tag{9}$$

to update their beliefs. Their belief that a country is dangerous is given by

$$\pi_{hdt} = \Pr(s_{dt} = 1 \mid \Psi_{hdt}, \hat{\theta}_d, \hat{\eta}_{d0}, \eta_{d1}).$$

which, again, evolves according to a recursion based on Bayes rule

$$\pi_{dt} = \frac{E_{t-1}\left[\pi_{dt}\right]}{E_{t-1}\left[\pi_{dt}\right] + \left[1 - E_{t-1}\left[\pi_{dt}\right]\right] \lambda\left(B_{hdt}, N_{hdt}\right)}$$

where, as before, $E_{t-1}\left[\pi_{dt}\right]$ is derived from the Markov chain governing the underlying categorical state.

One of the key predictions from this model is that observing *non-violent news* reporting about a country will lead potential tourists to update their belief that a country is safe. As $\hat{\eta}_1 > \hat{\eta}_0$, tourists will increase the probability that they attach to a place being dangerous if B_{hdt} increases. However, since $\hat{\eta}_0 > 0$ news about violence against tourists does not immediately give away to believing that a destination is unsafe. Context matters and the non-linearity of the model implies that there is a natural "tipping point" in equation (9) as a function of B_{hdt} relative to N_{hdt} at which tourists attach a much larger probability to a country being dangerous. This feature of the model allows it to account for the sharp changes in beliefs in response to news that are needed to explain patterns in the spending data.

In our model both sophisticated and naïve tourists care about the same underlying state when deciding on their holidays. It is only their information set that differs. In this way we have tied together objective violence as a manifestation of the state and news reporting as an informative signal of the state. In the appendix we show that there is a relationship between the objective true state and the posterior belief held by naïve tourists.[28] But beliefs based on news also deviate from those based on the history of violence. Such differences are interesting and show why, through the lens of the model, news reporting generates dyad-specific beliefs.

4.2 Fitting the Model

Putting all elements of the model together, the beliefs of tourists overall are a weighted average of both types of tourists. Specifically, we suppose tourist spending depends on

$$\hat{P}_{hdt} = \chi \Pi_{dt} + (1-\chi)\,\pi_{hdt} \tag{10}$$

where the parameter $\chi \in [0,1]$ reflects the proportions of potential tourists who are sophisticated (as opposed to naïve). In addition we assume that there are different points in time at which tourists book their holidays so that the overall relevant beliefs are given by $\sum_{\tau=0}^{-9} \omega_\tau \hat{P}_{hdt-\tau}$. Substituting equation (10) into (6) yields the following empirical specification:

$$y_{hdt} = \alpha_{hd} + \alpha_{ht} + \alpha_{dm} + \xi \sum_{\tau=0}^{-9} \omega_\tau \left(\chi \Pi_{dt-\tau} + (1-\chi)\,\pi_{hdt-\tau}\right) + \varepsilon_{hct}. \tag{11}$$

The model-based approach differs from equations (2) and (3) in three ways. First, the belief estimates, (Π_{dt}, π_{hdt}), are both heterogeneous across countries and non-linear in their responsiveness to violence and news data. Second they depend on the entire history of violence rather one period lagged values and third, they allow a lag structure to reflect the timing of travel decisions. At the same time the weights (ω, χ) reflect the importance of different kinds of tourist behavior for overall spending.

Table 6 explores how well our estimates of the two sets of constructed beliefs

[28] Appendix Figure A6 reports the posterior distribution of π_{dt} for months that we classify as relatively dangerous ($\Pi_{dt} > \frac{1}{2}$) and safe ($\Pi_{dt} \leq \frac{1}{2}$) destination/months. Both distributions have full support but the density of π_{dt} has a much thicker tail during dangerous months.

$\{\Pi_{dt}, \pi_{hdt}\}$ explain variations in aggregated spending. In column (1) of Table 6, we report the relationship between aggregated spending and Π_{dt-1}, i.e. supposing that $\chi = 1$ and $\omega_{-1} = 1$ in equation (10). On average, spending falls by about 20.8 percent when beliefs Π_{dt-1} increase from 0 to 1, i.e. when a destination goes from being viewed as completely safe to completely dangerous. This magnitude is in the same ballpark as the reduced-form results reported in Table 2. But unlike the estimates based on (2), recall that Π_{dt-1} moves as in Figure 6 and therefore reacts much more strongly to some changes in violence than others. Moreover, effects coming through Π_{dt-1} are also naturally heterogeneous across destination countries.

(Table 6)

Column (2) focuses on responsiveness of spending to π_{hdt-1}, i.e. imposing $\chi = 0$ and $\omega_{-1} = 1$. We now get a fall of 36.4 percent if the news-based belief that a destination country is dangerous within a dyad moves from 0 to 1. This is true even though most dyads with high values of π_{hdt} also have high values of Π_{dt} so that these two effects are complements with π_{hdt} increasing the intensity of the impact of violence on tourism spending. In column (3) we estimate π_{hdt} based on news reporting on fatalities rather than targeting tourists. And although, as in the reduced-form results, the impact of news reporting is somewhat smaller in magnitude, it moves in the same direction.

We now explore the weights that give the best fit to the data using a grid search over the weights in equation (11) to maximize goodness of fit.[29] We find that $\hat{\omega}_0 = \hat{\omega}_1 = 0.2$ so that 20 percent of spending is driven by contemporaneous beliefs and 20 percent are coming from the first lag. After that, the weight based on the best fit falls (the weight sequence is 0.15, 0.1, 0.1, 0.1, 0.05, 0.05, 0.05). We find that the weight on sophisticated tourists that best fits the data is $\hat{\chi} = 0.4$, i.e. two in five tourists are sophisticated. We will use these estimates of the weights and $\hat{\xi}$ to quantify the impact of news on spending in the next section.

Putting this together, we find that "optimal" weighted average reported in column (4) suggests that if all tourists switched their categorical beliefs that a destination is

[29] See Appendix B for more details.

dangerous from zero to one, then spending would fall by about 75 percent. Of course, this is quite an extreme thought experiment but perhaps not so extreme when we think of the cases such as Tunisia where there were quick upticks in violence that could not reasonably have been anticipated by potential tourists.

4.3 Simulation of a News Shock

A crucial difference between sophisticated and naïve approaches to belief formation in the model is that the probability that a destination is more likely to be regarded as safe by naïve tourists if there is more non-violent (other) news coverage, i.e. $N_{hdt} - B_{hdt}$. Figure 7 illustrates the role of other news by considering an outbreak of violence on tourists (at date 0) which changes beliefs from $\Pi_{d,-1} = 0$ to $\Pi_{d,0} = 1$ for one month. This yields the dashed line in both panels of Figure 7. The immediate effect is that the 20 percent of tourists which react immediately to danger ($\omega_0 = 0.2$) do not travel to the destination and tourism spending falls by around six percentage points. The dashed line shows the persistent effect on tourism spending, i.e. the effect of $\Pi_{d,0} = 1$ falls only slowly because most tourists book their travel in advance.

(Figure 7)

We then show the *additional* impact of news reporting in a scenario in which this switch in the sophisticated beliefs is accompanied by bad news $B_{hd0} = 1$. To illustrate the importance of other news, $N_{hdt} - B_{hdt}$, we contrast two levels of background reporting $N_{hd0} \in \{0, 100\}$. Panel A shows the effect of bad news on tourism spending with no other news, $N_{hdt} = 0$, is a further eight percentage points in spending. Again, because tourists book their holidays in advance this effect persists. However, with $N_{hd0} = 100$, the news about tourist violence is "drowned out" by other news and the impact of $B_{hd0} = 1$ is reduced dramatically. This kind of scenario is not atypical of the reporting landscape for tourist violence in a country like Israel where there is a lots of other news coverage.

This vividly illustrates the importance of background news in "distracting" tourists or "putting things into perspective" for tourists when they rely exclusively on news coverage to form their beliefs - even when such tourists update using Bayes rule. The bias in their beliefs is due to their failing to explore a wider set of news sources. By restricting their updating to domestic news sources, their beliefs are biased in a similar way to what would happen if tourists were to update using the model of Bordalo et al. (2016) in which destination countries are stereotyped as dangerous if they are covered by bad news even without any other background news coverage.

4.4 The Aggregate Economic Impact of Reporting

To quantify the news effect we can contrast the average effect that is coming from sophisticated tourists, $\hat{\hat{\xi}} \sum_{\tau=0}^{-9} \hat{\omega}_\tau \hat{\chi} \hat{\Pi}_{dt-\tau}$, and the overall effect, $\hat{\hat{\xi}} \sum_{\tau=0}^{-9} \hat{\omega}_\tau \hat{P}_{hdt-\tau}$. We can think of the difference between these two as the news effect, $\hat{\hat{\xi}} \sum_{\tau=0}^{-9} \hat{\omega}_\tau \left(1 - \hat{\chi}\right) \hat{\pi}_{dt-\tau}$. In Figure 8 we show the effect based on beliefs of sophisticated tourists using a grey line and the overall effect as a black line.

The left-hand panel in Figure 8 shows the results for Tunisia which shows that a large part of the variability in tourism spending comes from belief change by sophisticated tourists, i.e. is not dyad-specific. However, there is a visible news effect and in 2015 it alone is responsible for a spending decline of about 15 percent. This illustrates the influence that reporting may have had a dramatic impact on tourism for Tunisia in that year. In the right-hand Panel we show the same data for Egypt. Again, we get some news effect but it is nowhere nearly as large as the main effect from sophisticated tourists. This is a dramatic illustration of the crowding out effect that we illustrated in Figure 7.

(Figure 8)

The estimates in Figure 8 suggest material losses to the economy in all four countries that we study. The World Bank reports that tourism revenues in 2010 were 3.48 Billion USD in Tunisia, 5.6 Billion USD in Israel, 13.63 Billion USD in Egypt and 26.3 billion USD in Turkey. Back of the envelope calculations based on the estimates in this section indicate losses between 2011 and 2016 of over 35 billion USD due to violence with in excess of 10 billion USD being due to negative news reporting.[30] That said, Egypt and Tunisia are predicted to have recovered the losses towards the end of the sample period.

[30] For calculations see the Appendix C.

Figure 9 explores how well the model-based approach fits the data. The left-hand panel illustrates the predicted effect, averaged over all origin countries, for Tunisia based on (11) and compares it to the spending residuals. The model captures both the early decline and recovery at the beginning of the Arab spring. However, the most striking observation is for 2015 where it accurately captures both the decline and recovery in spending.

(Figure 9)

The model-based prediction compares favorably with that from the reduced-form model as shown in the right-hand panel of Figure 9. For this we use the estimated effects, $\xi_1 n_{hdt-1} + \xi_2 v_{hct-1}$ averaged over origin countries based on Table 3. Although some of the broad patterns are visible, the fit to the data is notably inferior to that in the left-hand panel, failing to reproduce the timing and magnitude of the fluctuations in spending. This is particularly noticeable during the Arab spring and getting the timing right in sudden expenditure declines in 2015. Thus Figure 9 supports the utility of an approach which models patterns of belief formation alongside a reduced-form approach.

5 Conclusions

The core finding of the paper is that there is a robust negative relationship between violence, reporting on violence and tourism spending based on a sample of five destination and fifty-seven origin countries. This is established leveraging novel data sources on both aggregated spending and news coverage. A key finding is that the effect of violence and news coverage varies markedly across both destination and origin countries. To explain this, we have fitted a specific model of belief formation to study patterns in the data. In the best fit to the data, we find that about a third of the weight in terms of updating beliefs comes from country-specific news reporting but there is significant heterogeneity across countries and events.

The paper contributes to an emerging literature which explores the power of the media in influencing economic decisions. Citizens rely heavily on the media as a source of information when deciding where and when to travel. Our supervised machine learning method of identifying specific negative news linked to violent events allowed us to study this. We find that there is significant country-level heterogeneity in responses to violence are attributable to negative news reporting. In particular, we find that sudden slumps in spending with gradual recovery are best explained by a media effect. The media is indeed powerful in affecting international flows of tourists.

It is often claimed that perceptions matter for more than tourism. Negative coverage of the prospects for African countries create a climate of opinion among corporate boards and shareholders which could affect the allocation of FDI. This is particularly poignant in an era where social media and the potential for fake news is attracting increasing attention and for a region which is economically not well integrated (Rouis and Tabor, 2012). How far news biases have real aggregate economic consequences has yet to be studied but is ripe for investigation.

The basic ideas and methods developed here can be extended to a number of additional contexts. We have cautiously identified the effects of violence and its reporting *within* a set of five countries. But this leaves open the question of whether tourists divert their spending to other countries or even choose to stay at home. So there can be gainers and losers from violence. To study this would require aggregated spending data from a broader range of destination countries. We have also looked at quite extreme violent events because their news effect is easier to identify. It would be interesting to look at other forms of crime perpetrated on tourists. This too could have an impact on tourism via a news reporting channel. For this, destinations such as the Caribbean and Latin America would be particularly interesting.

Finally, our paper contributes to wider debates about forces that could lead to a reversal in globalization. Given that increased international travel has been a significant component of global integration, determinants of tourism are important not just in terms of generating traditional economic gains from trade but also in creating greater cross-cultural understanding. To the extent that security concerns increase the perceived costs of travel, politics may therefore have an important impact on this aspect of international integration. And the results in this paper suggest that how the media chooses to report these risks has a role to play in this process.

References

Abadie, A. and J. Gardeazabal (2003). The economic costs of conflict: A case study of the Basque Country. *American Economic Review 93*(1), 113–132.

Acemoglu, D., S. Naidu, P. Restrepo, and J. A. Robinson (2019). Democracy Does Cause Growth. *Journal of Political Economy 127*(1), 47–100.

Adams, W. C. (1986). Whose Lives Count? TV Coverage of Natural Disasters. *Journal of Communication 36*(2), 113–122.

Allcott, H. and M. Gentzkow (2017). Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives 31*(2), 211–236.

Amodio, F. and M. Di Maio (2018). Making Do With What You Have: Conflict, Input Misallocation and Firm Performance. *The Economic Journal 128*(615), 2559–2612.

Arezki, R., V. A. Ramey, and L. Sheng (2017). News Shocks in Open Economies: Evidence from Giant Oil Discoveries. *The Quarterly Journal of Economics 132*(1), 103–155.

Azeredo da Silveira, R. and M. Woodford (2019). Noisy Memory and Over-Reaction to News. *AEA Papers and Proceedings 109*, 557–561.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics 131*(4), 1593–1636.

Barrera, O., S. Guriev, E. Henry, and E. Zhuravskaya (2017). Facts, Alternative Facts, and Fact Checking in Times of Post-Truth Politics. *CEPR Working Paper*, 1–70.

Becker, G. S. and Y. Rubinstein (2011). Fear and the Response to Terrorism: An Economic Analysis. *CEP Discussion Paper*, 1–90.

Becker, S. O. and L. Pascali (2019). Religion, Division of Labor, and Conflict: Anti-Semitism in Germany over 600 Years. *American Economic Review 109*(5), 1764–1804.

Besley, T. and R. Burgess (2002). The Political Economy of Government Responsiveness: Theory and Evidence from India. *The Quarterly Journal of Economics 117*(4), 1415–1451.

Besley, T., T. Fetzer, and H. Mueller (2015). The Welfare Cost of Lawlessness: Evidence from Somali Piracy. *Journal of the European Economic Association 13*(2), 203–239.

Besley, T. and H. Mueller (2012). Estimating the Peace Dividend: The Impact of Violence on House Prices in Northern Ireland. *American Economic Review 102*(2), 810–833.

Bordalo, P., K. Coffman, N. Gennaioli, and A. Shleifer (2016). Stereotypes. *The Quarterly Journal of Economics* (October), 1753–1794.

Bordalo, P., N. Gennaioli, Y. Ma, and A. Shleifer (2018). Over-reaction in Macroeconomic Expectations. *NBER Working Paper* (March).

Brodeur, A. (2018). The effect of terrorism on employment and consumer sentiment: Evidence from successful and failed terror attacks. *American Economic Journal: Applied Economics 10*(4), 246–282.

Burchardi, K. B., T. Chaney, and T. A. Hassan (2019). Migrants, Ancestors, and Foreign Investments. *The Review of Economic Studies 86*(4), 1448–1486.

Bursztyn, L., D. Cantoni, P. Funk, and N. Yuchtman (2017). Polls, the Press, and Political Participation: The Effects of Anticipated Election Closeness on Voter Turnout. *NBER Working Paper*.

DellaVigna, S. and E. Kaplan (2007). The fox news effect: Media bias and voting. *Quarterly Journal of Economics 122*(3), 1187–1234.

Donaldson, D. (2018). Railroads of the Raj: Estimating the Impact of Transportation Infrastructure. *American Economic Review 108*(4-5), 899–934.

Durante, R., P. Pinotti, and A. Tesei (2019). The Political Legacy of Entertainment TV. *American Economic Review 109*(7), 2497–2530.

Durante, R. and E. Zhuravskaya (2018). Attack When the World Is Not Watching? US News and the Israeli-Palestinian Conflict. *Journal of Political Economy 126*(3), 1085–1133.

Eggers, A. and A. Fouirnaies (2014). The Economic Impact of Economic News. *mimeo*.

Eisensee, T. and D. Strömberg (2007). News droughts, news floods, and US disaster relief. *Quarterly Journal of Economics 122*(2), 693–728.

Faber, B. and C. Gaubert (2016). Tourism and Economic Development: Evidence from Mexico's Coastline. *American Economic Review 109*(6), 2245–2293.

Fetzer, T. (2019). Can Workfare Programs Moderate Conflict? Evidence from India. *forthcoming, Journal of the European Economics Association*.

Feyrer, J. (2019). Trade and Income – Exploiting Time Series in Geography. *forthcoming, American Economic Journal: Applied Economics* (603), 1–43.

Fiske, S. T. (1998). Stereotyping, prejudice, and discrimination. In &. G. L. D. T. Gilbert, S. T. Fiske (Ed.), *The handbook of social psychology*, pp. 357–411. New York: McGraw-Hill.

Frankel, J. A. and D. Romer (2008). Does Trade Cause Growth? *American Economic Review 89*(3), 379–399.

Fryer, R. and M. O. Jackson (2008). A categorical model of cognition and biased decision making. *B.E. Journal of Theoretical Economics 8*(1).

Gentzkow, M. (2006). Television and Voter Turnout. *Quarterly Journal of Economics 121*(3), 931–972.

Gentzkow, M. and J. M. Shapiro (2011). Ideological Segregation Online and Offline. *The Quarterly Journal of Economics 126*(4), 1799–1839.

Hamilton, J. (1990). Analysis of Time Series Subject to Changes in Regime. *Journal of Econometrics 45*, 39–70.

Handel, B. and J. Schwartzstein (2018). Frictions or mental gaps: What's behind the information we (don't) use and when do we care? *Journal of Economic Perspectives 32*(1), 155–178.

Hansen, S., M. McMahon, and A. Prat (2018). Transparency and Deliberation Within the FOMC: A Computational Linguistics Approach*. *The Quarterly Journal of Economics 133*(2), 801–870.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2019). Firm-Level Political Risk: Measurement and Effects. *The Quarterly Journal of Economics 134*(4), 2135–2202.

Iaria, A., C. Schwarz, and F. Waldinger (2018). Frontier Knowledge and Scientific Production: Evidence from the Collapse of International Science. *The Quarterly Journal of Economics 133*(2), 927–991.

Japkowicz, N. and S. Stephen (2002). The class imbalance problem: A systematic study1. *Intelligent Data Analysis 6*(5), 429–449.

Jetter, M. (2017). Terrorism and the Media : The Effect of US Television Coverage on Al-Qaeda Attacks. *IZA Discussion Paper* (10708).

Jha, S. and M. Shayo (2019). Valuing Peace: The Effects of Financial Market Exposure on Votes and Political Attitudes. *Econometrica 87*(5), 1561–1588.

Manacorda, M. and A. Tesei (2016). Liberation Technology: Mobile Phones and Political Mobilization in Africa. *mimeo 785*(March 2016), 1–72.

Manela, A. and A. Moreira (2017). News implied volatility and disaster concerns. *Journal of Financial Economics 123*(1), 137–162.

Melitz, M. J. and D. Trefler (2012). Gains from trade when firms matter. *Journal of Economic Perspectives 26*(2), 91–118.

Mueller, H. (2012). Growth Dynamics: The Myth of Economic Recovery: Comment. *American Economic Review 102*(7), 3774–3777.

Mueller, H. and C. Rauh (2017). Reading Between the Lines: Prediction of Political Violence Using Newspaper Text. *American Political Science Review 2*(October), 1–18.

Mullainathan, S. and A. Shleifer (2005). The Market for News. *American Economic Review 95*(4), 1031–1053.

Neumayer, E. (2004). The Impact of Political Violence on Tourism. *Journal of Conflict Resolution 48*(2), 259–281.

Pedregosa, F., V. Michel, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, J. Vanderplas, D. Cournapeau, G. Varoquaux, A. Gramfort, B. Thirion, O. Grisel, V. Dubourg, A. Passos, M. Brucher, M. Perrot, and E. Duchesnay (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research 12*, 2825–2830.

Persson, T. and G. Tabellini (2009). Democratic Capital: The Nexus of Political and Economic Change. *American Economic Journal: Macroeconomics 1*(2), 88–126.

Prat, A. and D. Strömberg (2011). The Political Economy of Mass Media. *CEPR Discussion Paper*.

Ramey, V. A. (2011). Identifying government spending shocks: It's all in the timing. *Quarterly Journal of Economics 126*(1), 1–50.

Rouis, M. and S. R. Tabor (2012). *Regional Economic Integration in the Middle East and North Africa*.

Singer, E. and P. M. Endreny (1993). *Reporting on Risk: How the Mass Media Portray Accidents, Diseases, Other Hazards*. Russell Sage Foundation.

Snyder, J. M. and D. Strömberg (2010). Press coverage and political accountability. *Journal of Political Economy 118*(2), 355–408.

Stromberg, D. (2004). Radio's Impact on Public Spending. *The Quarterly Journal of Economics 119*(1), 189–221.

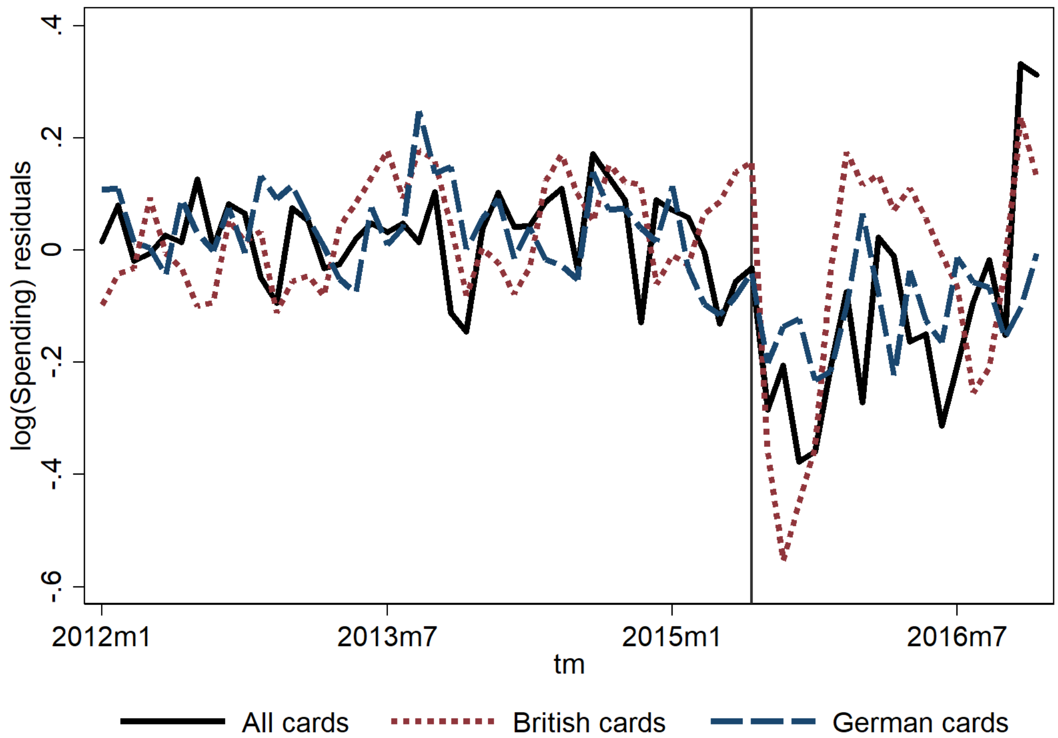
Strömberg, D. (2015). Media and Politics. *Annual Review of Economics 7*(1), 173–205.

Tversky, A. and D. Kahneman (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology 5*(2), 207–232.

Tversky, A. and D. Kahneman (1974). Judgment under Uncertainty: Heuristics and Biases. *Science 185*(4157), 1124–1131.

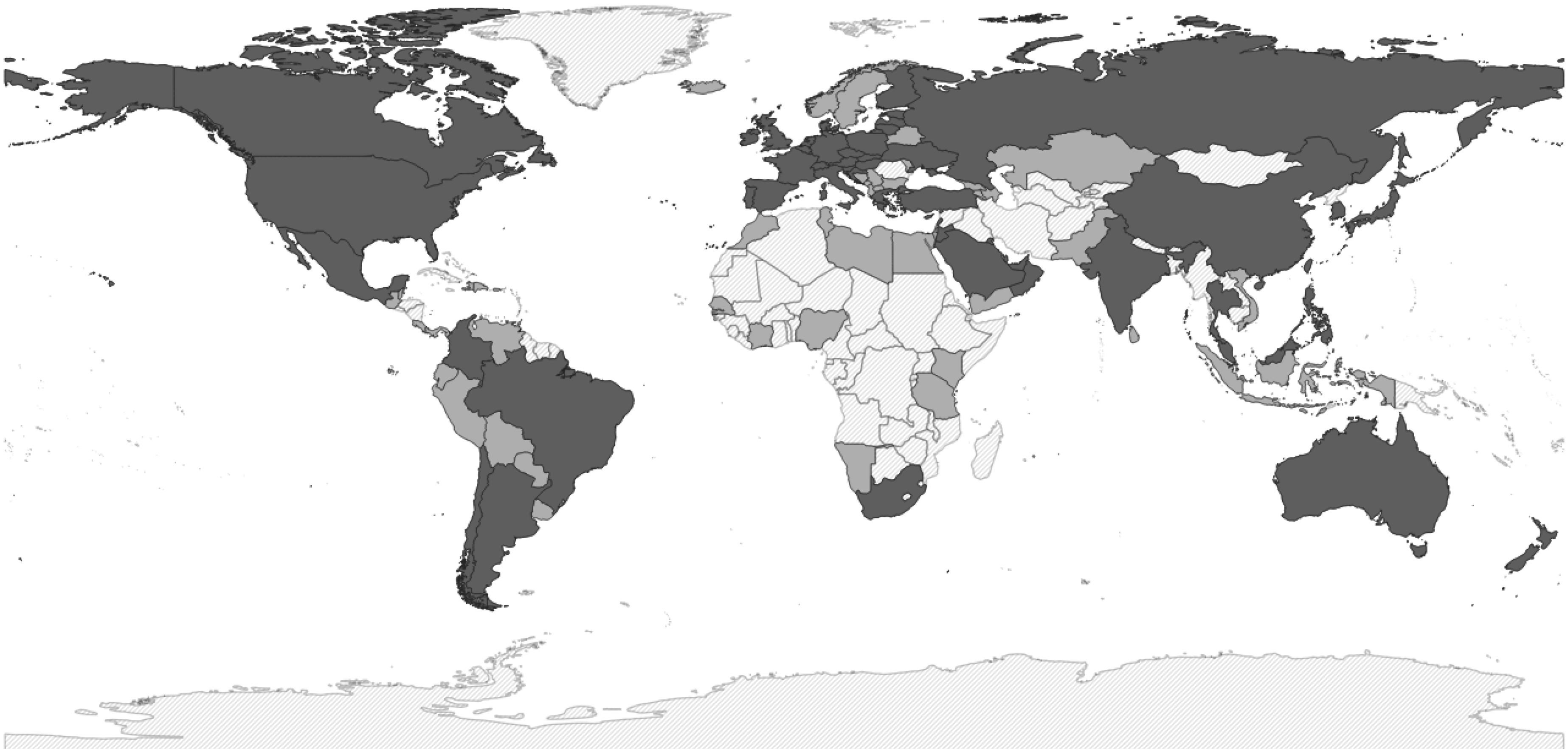
WTTC (2018). Travel & Tourism Power and Performance - September 2018. pp. 1–23.

Figure 1: Overall aggregated spending patterns of British- and German-issued cards in Tunisia in the wake of the Sousse attack)



Notes: The solid black line presents residuals of a regression of the log of aggregated card spending removing destination country fixed effects as well as destination-specific seasonality. The other two lines plot residuals of a regression of the log card spend for German- and British-issued cards in Tunisia over time, having removed dyad fixed effects, issuing country by time fixed effects and destination by month fixed effects. The drop in tourism spending is markedly larger for British-issued cards.

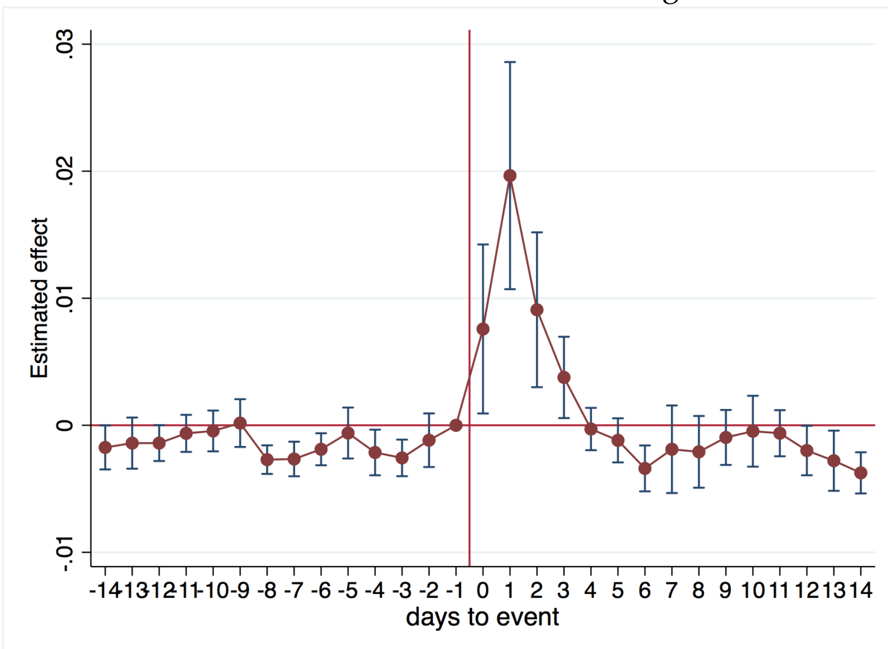
Figure 2: Map of countries included in our estimation samples across the exercises



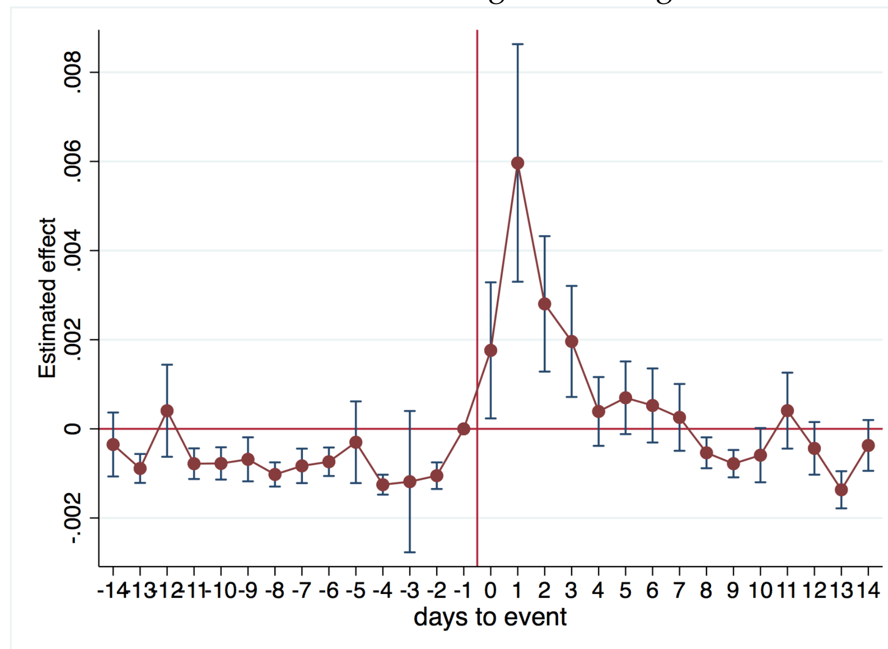
Notes: Figure indicates the origin countries included in our estimating sample. Dark-shaded are countries for which both newspaper and aggregated spending data is available, lightly shaded areas are countries for which only aggregated spending data is available.

Figure 3: GTD Events and Reporting Activity: No evidence of diverging pre-trends prior to events

Panel A: Share of articles classified as indicating fatalities

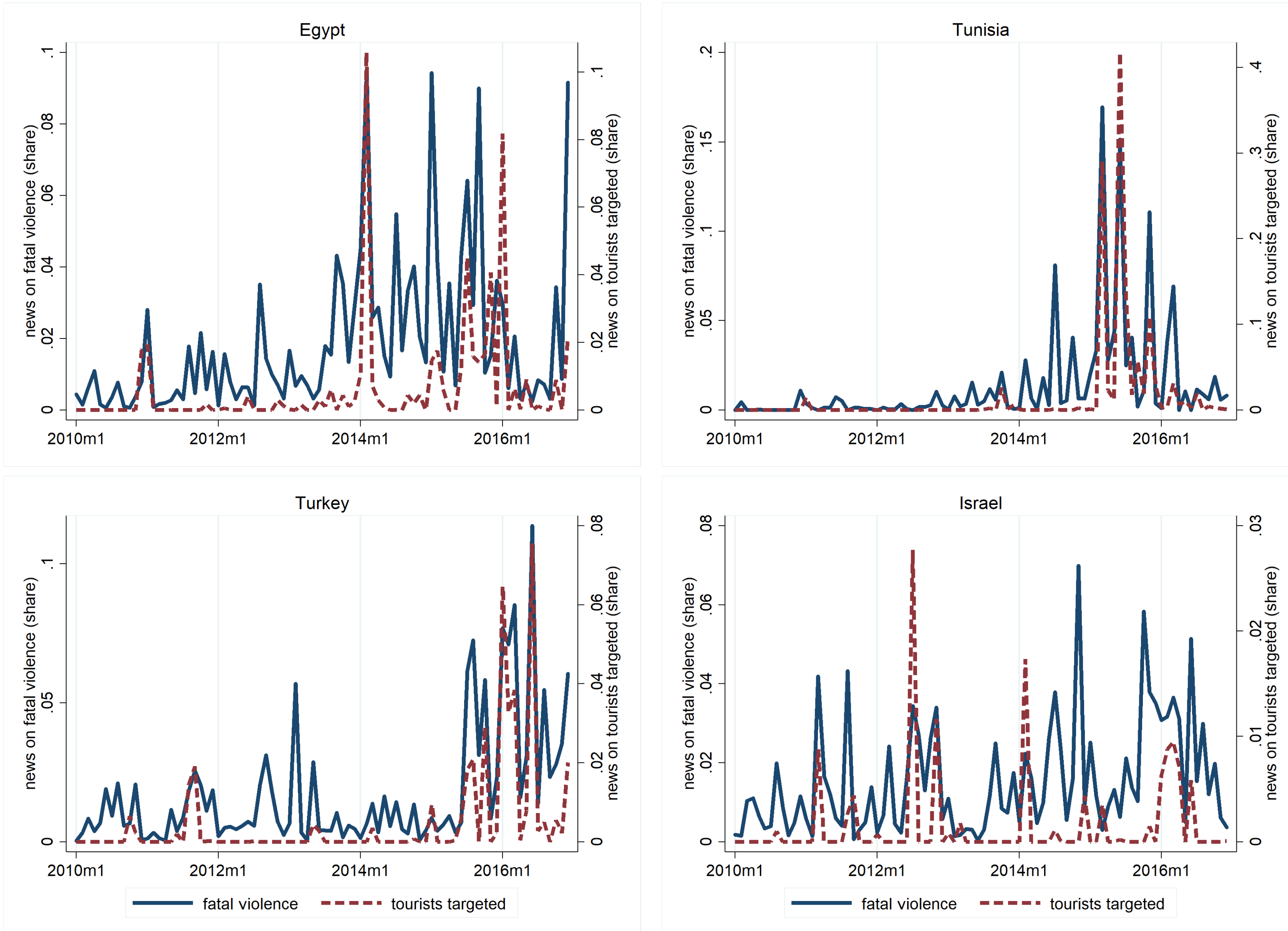


Panel B: Share of articles indicating tourist targeted



Notes: Figure plots point estimates from a regression that absorbs event, reporting dyad and day fixed effects. The plotted point estimates capture the timing of reporting on a dyad specific to the timing of an individual event recorded in the GTD dataset. 90% confidence intervals obtained from clustering standard errors at the dyad level are indicated.

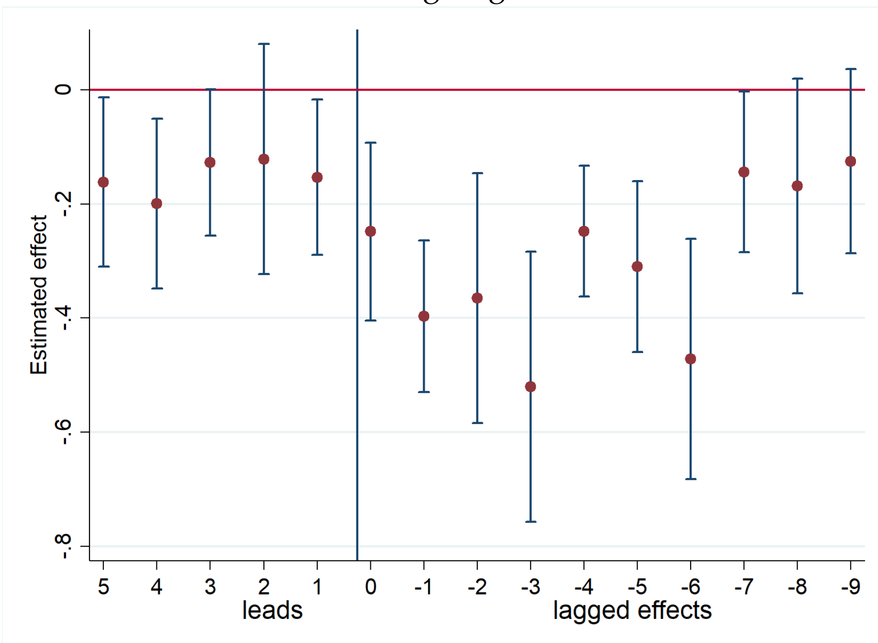
Figure 4: Average Share of Articles on Fatal Violence and Violence Against Tourists



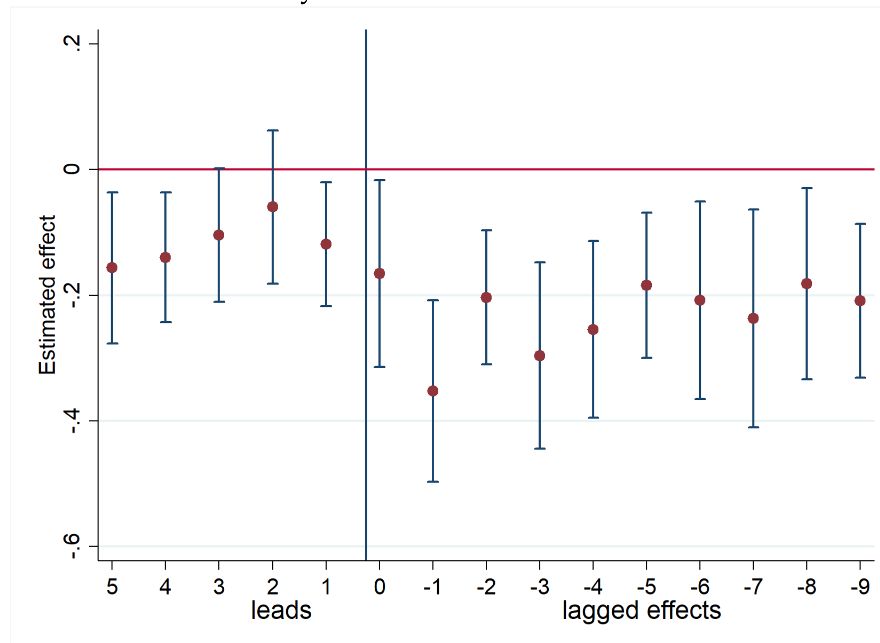
Notes: Figure plots the time series variation in the share of (any) fatal violence or on violence directed towards tourists across four main countries.

Figure 5: Leads and Lagged Effect of Tourist Violence on Tourism Spending

Panel A: News on tourist being targeted

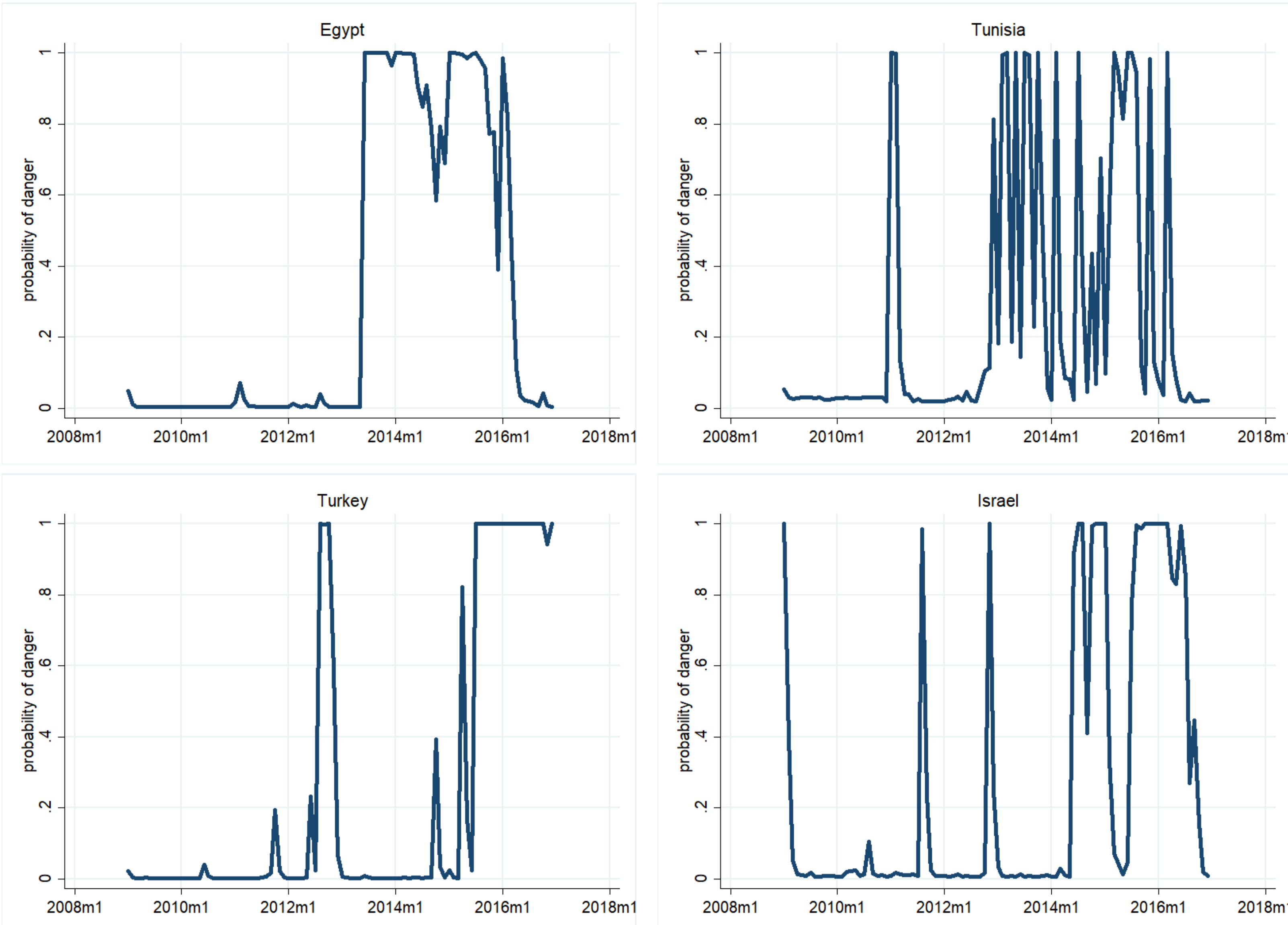


Panel B: News on any fatal violence



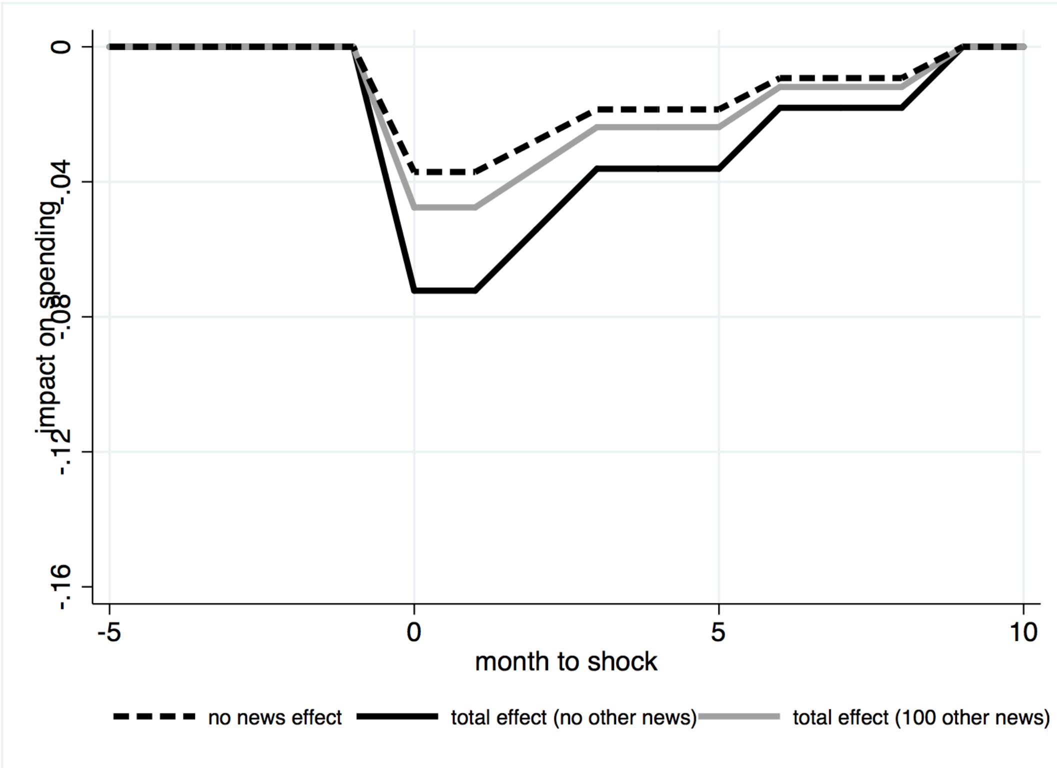
Notes: Figure plots the effect of different leads and lags of the main tourist violence measure on card spending. The underlying regression controls for dyad fixed effect, issuing-country by time fixed effect and destination by month. 95% confidence bands obtained from clustering the data at the dyad level are indicated.

Figure 6: Markov Chain Fitted Probability of Danger Across Sample Countries



Notes: Figures plot out the probability of danger as implied by the fitted Markov chain across the four main tourist destinations in our data.

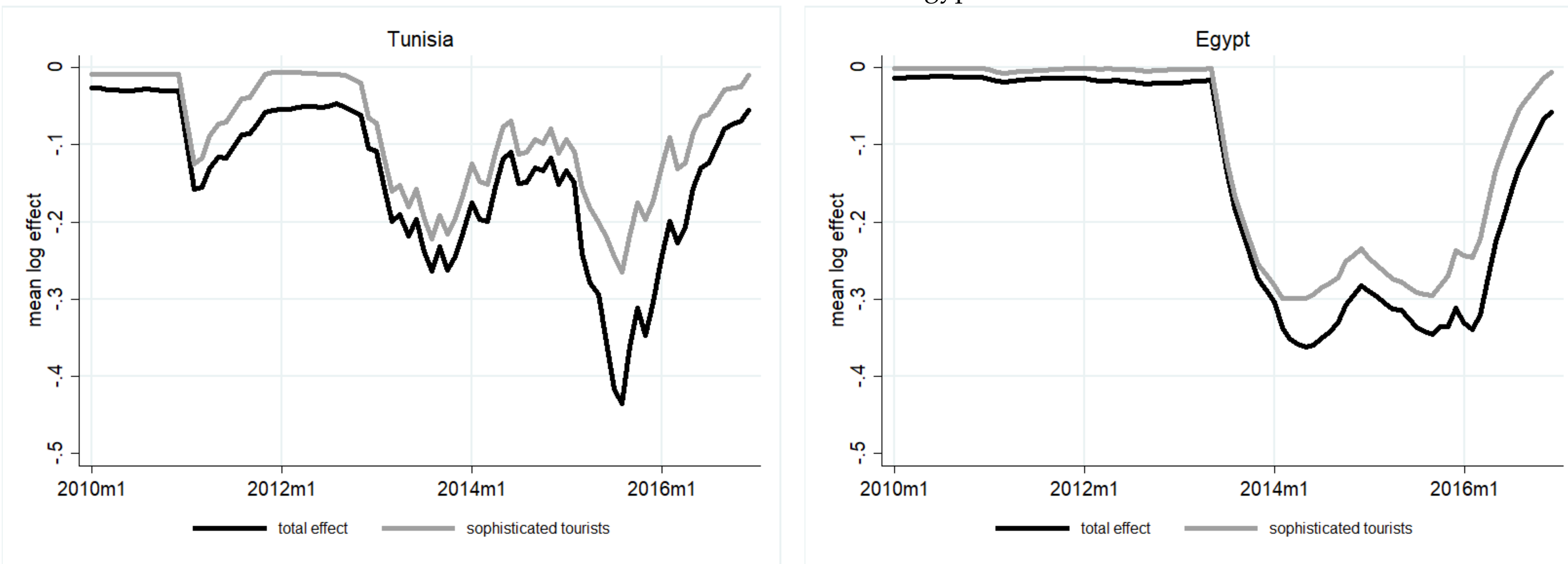
Figure 7: Simulated effect of violent news shock and moderating impact of other news coverage)



Notes: The figure plots out the model-implied impact of a violent event (dashed line). The solid grey line presents the total effect that incorporates the media-coverage effect with 100 other news items on topics unrelated to violence. The solid black line presents the total effect if there is no other media coverage, attenuating the impact on beliefs.

Figure 8: Tunisia and Egypt model-based effects

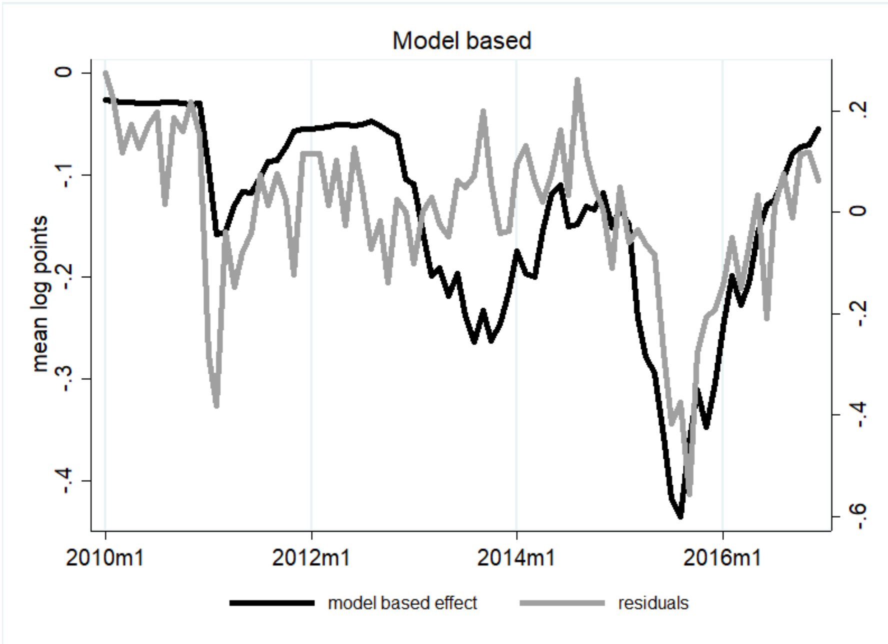
Panel A: Tunisia *Panel B*: Egypt



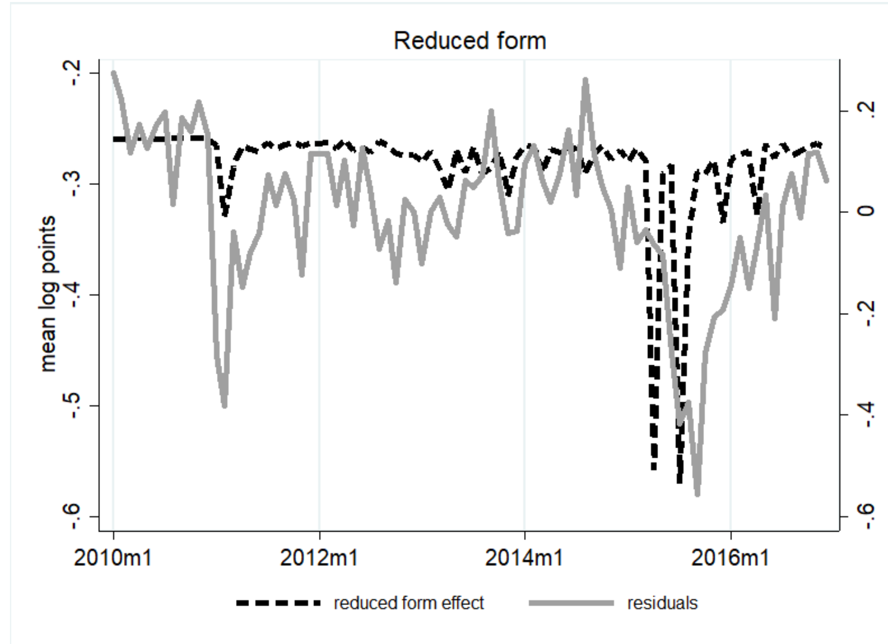
Notes: Figure plots the overall model-based impact of violent news shocks on tourism spending for Tunisia (left) and Egypt (right). The solid black line presents the total effect while the grey line presents the effect implied by modelled sophisticated tourists.

Figure 9: Comparison of model- and reduced-form implied effects on tourism spending in Tunisia

Panel A: Model based



Panel B: Reduced form



Notes: The left figure plots mean of the model-based estimated effect on tourism spending against the patterns in the average residualized data after removing dyad-, origin-by-time and destination by month fixed effects. The right figure plots the same residuals against the implied mean reduced effects that would be captured in a pure reduced-form regression studied, for example, in Table 3.

Table 1: Summary Statistics

	Mean	SD	Observations
ACLED Events	0.612	0.934	31212
UCDP Events	0.278	0.968	55620
GTD Events	0.404	0.904	55620
ICEWS armed violence events	0.627	0.925	55105
GDELT armed violence events	0.718	0.983	49440
News on tourists targeted (count of articles)	0.035	0.856	30495
News on tourists targeted (share of all articles)	0.002	0.033	30495
News on violence with fatalities (share of all articles)	0.015	0.068	30495
Any tourist killed	0.001	0.031	61800
Same region x Any Casualties	0.006	0.075	61800
Common language x Any Casualties	0.007	0.082	61800

Table 2: Effect of Country-level Violence measured by different event data sets on tourism spending and active cards

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	log(Spending)					log(Cards)				
UCDP Events	-0.040***					-0.034***				
	(0.010)					(0.008)				
GTD Events		-0.075***					-0.076***			
		(0.017)					(0.016)			
ICEWS armed violence events			-0.068***					-0.054***		
			(0.020)					(0.019)		
GDELT armed violence events				-0.065***					-0.047***	
				(0.016)					(0.015)	
Armed violence component 1					-0.067***					-0.053***
					(0.017)					(0.017)
Armed violence component 2					-0.041***					-0.034**
					(0.014)					(0.015)
Armed violence component 3					0.018					0.010
					(0.015)					(0.015)
Armed violence component 4					-0.031**					-0.039***
					(0.013)					(0.014)
Observations	42268	42268	42268	42268	42268	42313	42313	42313	42313	42313
R2	.947	.947	.947	.947	.947	.969	.97	.969	.969	.97
Dest./Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Origin/Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Dyad FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at destination by time level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Explanatory variables are lagged by one month to account for the lagged response of tourism to events. We also divide all explanatory variables by their standard deviation so that the coefficients can be interpreted as the response of spending to one standard deviation increase in violence regardless of the violence measure. Components are coming from principal component analysis of all different violence data sub-categories.

Table 3: News Reporting and Tourism Spending Reduced Form Results

	(1)	(2)	(3)	(4)	(5)	(6)
	log(Spending)			log(Numer of cards)		
Panel A: News on tourist being targeted						
News on tourists targeted (share of all articles)	-0.552***	-0.529***	-0.205**	-0.628***	-0.617***	-0.192***
	(0.092)	(0.098)	(0.090)	(0.068)	(0.074)	(0.066)
Observations	23859	23859	23859	23869	23869	23869
R2	.966	.967	.972	.97	.971	.979
Panel B: News on any fatal violence						
News on violence with fatalities (count of articles)	-0.458***	-0.337***	-0.196**	-0.364***	-0.269***	-0.061
	(0.092)	(0.098)	(0.093)	(0.060)	(0.062)	(0.054)
Observations	23859	23859	23859	23869	23869	23869
R2	.966	.967	.972	.97	.971	.979
Dyad FE	YES	YES	YES	YES	YES	YES
Origin/Time FE	YES	YES	YES	YES	YES	YES
Dest./Month FE	YES	YES	YES	YES	YES	YES
Event controls	NO	YES	NO	NO	YES	NO
Dest./Time FE	NO	NO	YES	NO	NO	YES

Notes: Robust standard errors clustered at destination/month level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Explanatory variables are lagged by one month to account for the lagged response of tourism to events and news. Event controls are the first four principal components combining the main country-level violence data series studied in Table 2 and Appendix Table A3.

Table 4: Evidence on Relative Nature of Reporting Measure

	(1)	(2)	(3)	(4)
		log(Spending)		
Panel A: News on tourist being targeted				
News on tourists targeted (count of articles)	-0.007**	-0.006**		
	(0.003)	(0.002)		
News on tourists targeted (share of all articles)	-0.512***	-0.494***		
	(0.095)	(0.101)		
News on tourists targeted (share of all articles) - first quartile			-0.005	0.051
			(0.051)	(0.048)
News on tourists targeted (share of all articles) - second quartile			-0.087*	-0.051
			(0.049)	(0.047)
News on tourists targeted (share of all articles) - third quartile			-0.160***	-0.123***
			(0.041)	(0.042)
News on tourists targeted (share of all articles) - fourth quartile			-0.304***	-0.297***
			(0.079)	(0.081)
Observations	23859	23859	23859	23859
R2	.966	.967	.966	.967
Panel B: News on any fatal violence				
Violent events with fatalities (count of articles)	-0.003	0.001		
	(0.002)	(0.003)		
News on violence with fatalities (share of all articles)	-0.422***	-0.351***		
	(0.097)	(0.102)		
News on violence with fatalities (share of all articles) - first quartile			-0.065	-0.019
			(0.047)	(0.044)
News on violence with fatalities (share of all articles) - second quartile			-0.063**	-0.018
			(0.025)	(0.025)
News on violence with fatalities (share of all articles) - third quartile			-0.085***	-0.035
			(0.024)	(0.025)
News on violence with fatalities (share of all articles) - fourth quartile			-0.113***	-0.069**
			(0.032)	(0.032)
Observations	23859	23859	23859	23859
R2	.966	.967	.966	.966
Dyad FE	YES	YES	YES	YES
Origin/Time FE	YES	YES	YES	YES
Dest./Month FE	YES	NO	YES	NO
Dest./Time FE	NO	YES	NO	YES

Notes: Robust standard errors clustered at destination/month level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Explanatory variables are lagged by one month to account for the lagged response of tourism to events and news. Event controls are the first four principal components combining the main country-level violence data series studied in Table 2 and Appendix Table A3.

Table 5: Instrumental Variable Regression of Reduced Form Effect: Instrumenting news coverage intensity with known casualty-distribution for select events

	(1)	(2)	(3)	(4)	(5)	(6)
	News on tourists targeted			News on any fatal violence		
Panel A: first stage with reporting spillovers						
Any tourist killed	0.181***	0.191***		0.063***	0.069***	
	(0.050)	(0.051)		(0.023)	(0.023)	
Contiguous country x Any Casualties		0.149***	0.147***		0.065**	0.064**
		(0.038)	(0.038)		(0.029)	(0.029)
Same region x Any Casualties		0.059**	0.058**		0.034*	0.033*
		(0.024)	(0.024)		(0.019)	(0.019)
Common language x Any Casualties		0.034**	0.033**		0.030***	0.030***
		(0.015)	(0.015)		(0.010)	(0.010)
R2	0.260	0.303	0.291	0.307	0.317	0.315
Panel B: Second stage: tourism spending						
News measure (share of articles)	-0.811	-0.790***	-0.787**	-3.032	-1.492**	-1.350*
	(0.601)	(0.291)	(0.333)	(2.880)	(0.723)	(0.738)
R2	0.967	0.967	0.967	0.963	0.966	0.966
Weak IV	11.265	15.611	15.331	3.121	7.792	8.516
Panel C: Second stage: number of active cards						
News measure (share of articles)	-1.188*	-1.109***	-1.088***	-4.443	-2.327***	-2.133***
	(0.663)	(0.297)	(0.323)	(3.989)	(0.771)	(0.758)
R2	.971	.971	.971	.961	.969	.969
Weak IV	11.3	15.6	15.3	3.12	7.79	8.52
Observations	23859	23859	23859	23859	23859	23859
Dyad FE	YES	YES	YES	YES	YES	YES
Origin/Time FE	YES	YES	YES	YES	YES	YES
Dest./Month FE	YES	YES	YES	YES	YES	YES
Event controls	YES	YES	YES	YES	YES	YES

Notes: Notes: Robust standard errors clustered at destination/month level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Explanatory variables are lagged by one month to account for the lagged response of tourism to events and news. Event controls are the first four principal components combining the main country-level violence data series studied in Table 2 and Appendix Table A3

Table 6: Calibrated Model of Tourism Beliefs and Tourism Activity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Spending)				log(Numer of cards)			
probability of danger (based on violence data)	-0.208***				-0.203***			
	(0.019)				(0.020)			
probability of danger (tourist news-based)		-0.364***				-0.367***		
		(0.051)				(0.049)		
probability of danger (fatal news-based)			-0.239***				-0.213***	
			(0.049)				(0.055)	
weighted probability of danger				-0.750***				-0.795***
				(0.060)				(0.066)
Observations	23859	23859	23859	23859	23869	23869	23869	23869
R2	.966	.966	.966	.967	.971	.971	.97	.972
Dyad FE	YES	YES	YES	YES	YES	YES	YES	YES
Origin/Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Dest./Month FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at destination/month level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix
"Terror and Tourism: The Economic Consequences of Media Coverage"

For Online Publication

Timothy Besley Thiemo Fetzer Hannes Mueller

December 17, 2019

This appendix is subdivided into four sections. Section A presents further robustness checks and additional results as figures or tables that were omitted from the main paper due to space constraints. Section B provides more details on the grid-search used. Section C provides more information on the calculations for the economic impact estimates. Lastly, Section D presents further description, results and details about the machine-learning approach used to classify the 450,000 news articles.

A Further results and robustness checks

A.1 Event Regression Evidence for News

Complementary to Figure 3 we run the following specification

$$p_{hdt} = \alpha_k + \alpha_{hd} + \alpha_t + \beta \times \text{Post}_{k,t} + \gamma_k \times (\text{Post}_{k,t} \times z_k) + \epsilon_{hdt} \qquad (12)$$

where we have defined a dummy variable $Post_{k,t} = 1$ for $\tau = 0, 1, 2$ for up to two days following a violent event. Estimating equation (12) also allows us to explore whether this average effect is heterogenous across a range of event characteristics z_k: the level of casualties, whether American's are among the casualties and attacks involving tourists.

We present results from specification (12) in Table A2. In columns (1) through (5) the dependent variable is our news coverage covering the share of articles on a day is classified as indicating violence with fatalities. In columns (6) to (10), the dependent variable is the share of articles classified as indicating violence against tourists. In columns (1) through (5) we observe that reporting increases sharply in the two days after an event. The increase is larger when there are more casualties (column 1) and if there any American casualties (column 2). Suicide attacks are also more heavily covered (column 3) as well as attacks where tourists are targeted (column 4). Column (5) shows that these all hold up when included together. In columns (6) through (10) we repeat the analysis with the more refined measure that captures the share of articles on a day indicating that tourists were targeted. Here, the most notable observation is column (9), which highlights that, if an event is classified by the GTD as having tourists as targets, the reporting measure increases sharply.

A.2 Event Study Evidence for Spending

To identify the effect of violence, the difference in difference approach relies on there being a common underlying trend in spending between places that experienced violent events and those did not. One way of exploring whether this is plausible is to use an event study approach. This will also give us more insight into the timing of the spending response to violent events.

For this purpose, we define an "event" as a month when casualties in the GTD dataset surpass a given threshold. Across the five destination countries there is a total of 256 country-by-month windows where an event with at least one casualty occurs (out of a total of the maximum possible 420 country-by-month windows from 2010-2016). For the empirical analysis, we focus on country-month event windows with at least 10 casualties, resulting in a total of 83 event months.

To look at the response in spending, we construct a twelve month window around each of these 83 event months which we denote by index k. We then use the following empirical specification to model the relationship between violent events and tourism activity:

$$y_{khdt} = \alpha_k + \alpha_{hd} + \alpha_{ht} + \sum_{\tau=-6}^{6} (\beta_\tau \times \text{Time to event month}_{k,t-\tau}) + \epsilon_{khd} \tag{13}$$

where, as above, y_{khdt} is the log of tourism spending in an event-month k from home country h in country d at date t. This specification includes event fixed effects α_k, dyad fixed effects α_{hd} and issuing country by time effects α_{ht}. As before, we adjust standard errors two way at the level of the dyad and event.

Estimating (13) permits us to trace out the patterns of aggregated spending around an event month. The results are depicted in Figure A4 for both log of spending and log of active card accounts. In both cases, there is no evidence of any anticipation of the event. Moreover, the observed pattern suggest a sharp contraction in card spending and the number of active cards with effects manifesting a month after an event occurred. Moreover, this occurs with a one month lag as in core specification. That said, it is clear that recovery from an event is quite slow.

In Appendix Table A4 we show that results are robust to dropping each country in turn, highlighting that the results are not an artefact of any of the five destination countries in our sample.

B Grid Search

In the grid search we proceeded as follows. We started from the estimation equation

$$y_{hdt} = \alpha_{hd} + \alpha_{ht} + \alpha_{dm} + \xi \sum_{\tau=0}^{9} \omega_\tau \left(\chi \Pi_{dt-\tau} + (1-\chi)\, \pi_{hdt-\tau} \right) + \varepsilon_{hct}. \tag{14}$$

and used different combinations of weights $\chi, \omega_\tau \in \{0, 0.05, 0.1, 0.15..., 1\}$ to calculate the term

$$\sum_{\tau=0}^{9} \omega_\tau \left(\chi \Pi_{dt-\tau} + (1-\chi)\, \pi_{hdt-\tau} \right).$$

which we then use as a regressor in equation 14. We pick the parameter values that yield the highest within R-squared. From this it should already be clear that assuming two different sets of weights on $\Pi_{dt-\tau}$ and $\pi_{hdt-\tau}$ would lead to an explosion of the complexity of the grid search. We therefore focus on one set of weights.

Note, that we did not impose any restrictions on the weights ω_τ. This is remarkable because we get the highest explanatory power with weights which (weakly) fall over time. In particular, we get the weight sequence

0.2, 0.2, 0.15, 0.1, 0.1, 0.1, 0.05, 0.05, 0.05.

For χ we get a value of 0.4 which implies that only 40 percent of the agents in our model are estimated to be sophisticated. However, sophisticated tourists will nonetheless drive most spending movements as the shifts in their beliefs are a lot more persistent.

We also ran robustness checks with a different model in which we used the level of violence, i.e. not only the state, as the variable that tourists are interested in. Results are very similar in that model so that we decided not to report it for brevity.

C Calculations of Total Loss

Assume that we have a monthly log spending before the violence which we call y_b. Assume that this takes some value $y_b = x$. The relationship between spending and violence is given as

$$y \approx x + \xi \sum_{\tau=0}^{9} \omega_\tau \left(\chi \Pi_{dt-\tau} + (1-\chi)\, \pi_{hdt-\tau} \right)$$

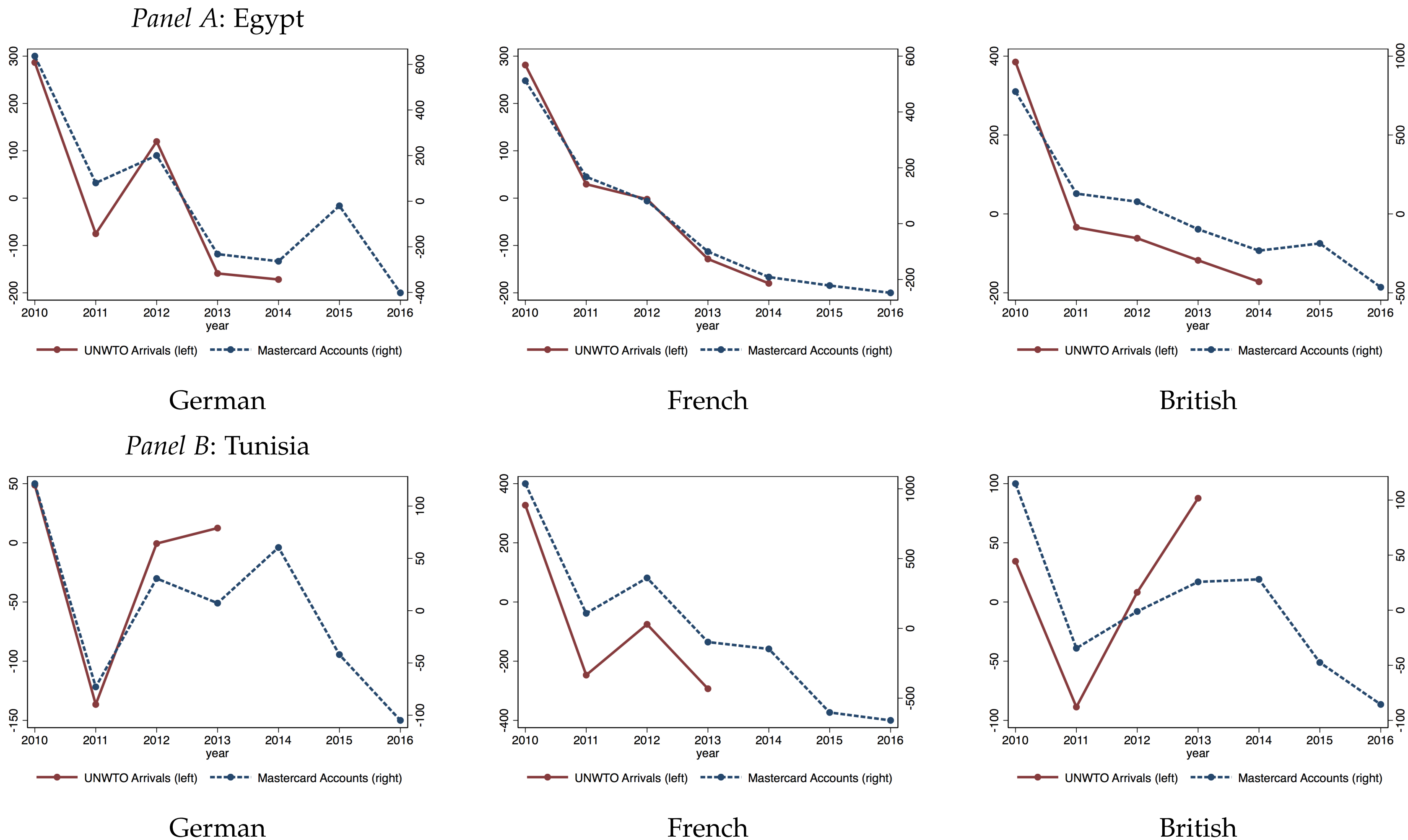
To compute the dollar value, we use the following transformation:

$$e^{y_b} - e^{y} = e^{x} - e^{x+\xi \sum_{\tau=0}^{9} \omega_\tau (\chi \Pi_{dt-\tau} + (1-\chi) \pi_{hdt-\tau})}.$$

We do this simply by giving every destination country the average treatment value coming out of all origin countries and applying it to the total tourism revenues measured at baseline in 2010.

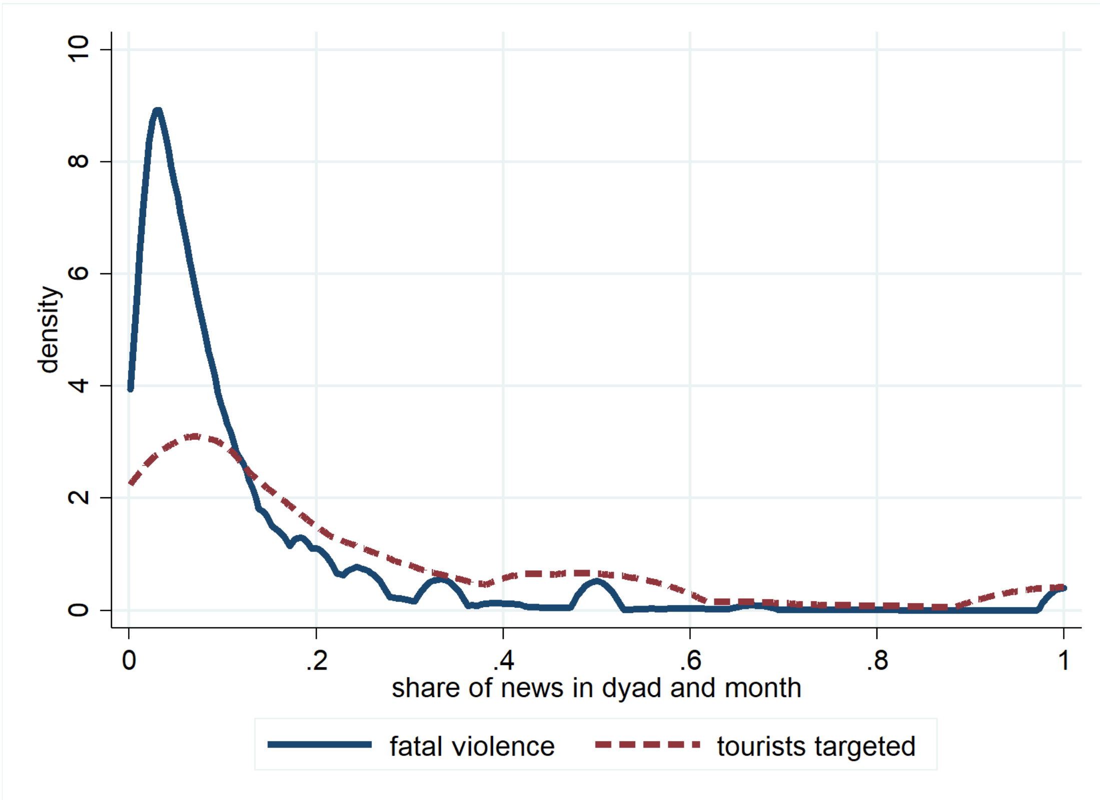
In the 72 months after 2010 we find the following average losses per month: 0.042 (0.027) billion USD in Tunisia, 0.063 (0.041) billion USD in Israel, 0.163 (0.13) billion USD in Egypt, 0.255 (0.171) billion USD in Turkey. Numbers in brackets indicate the losses from sophisticated tourists alone. This means a total loss of 37.66 billion USD and from news reporting alone 11.09 billion USD.

Figure A1: Validation of aggregated spending data as a proxy for tourist arrivals: comparing subsets of data from the UN World Tourism Organisation



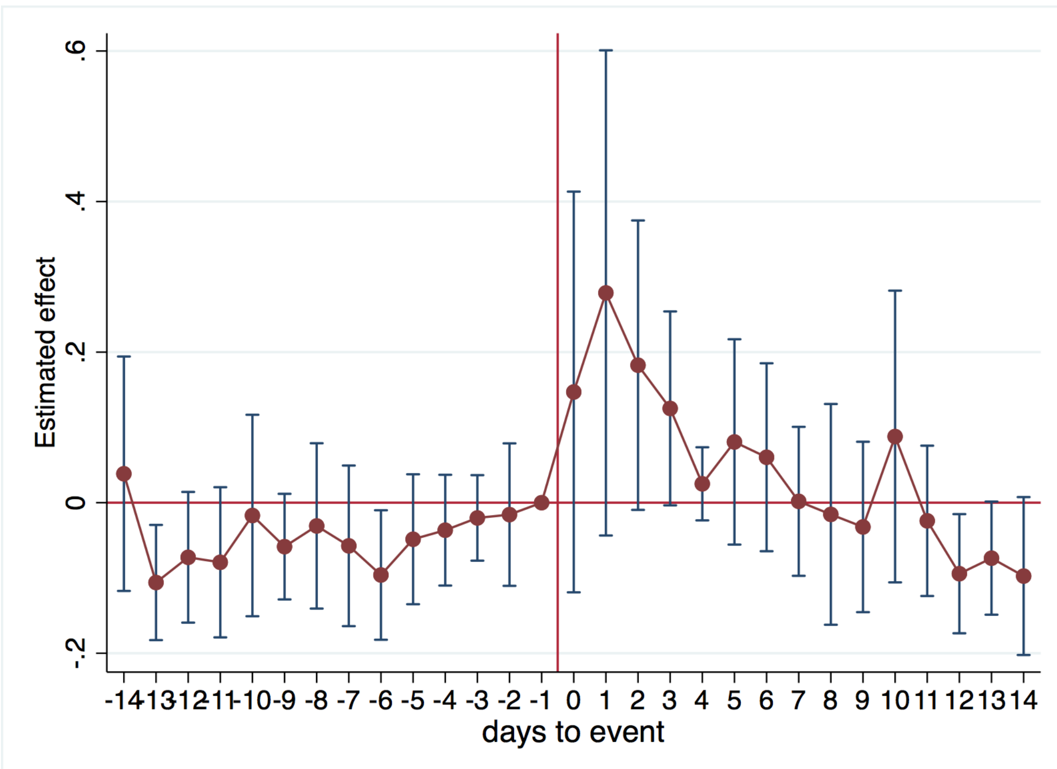
Notes: Figure plots dyadic data on tourist arrivals by destination country and by origin country, which is available annually for a small subset of countries from the UNWTO. The aggregate active accounts data has been further aggregated to the year level. The figures plotted are residuals obtained from removing dyad fixed effects as well as year fixed effects.

Figure A2: Distribution of Share of Articles on Fatal Violence and Violence Against Tourists



Notes: Figure plots kernel density plotting the distribution of share of newspaper reporting on (any) fatal violence or on violence directed towards tourists.

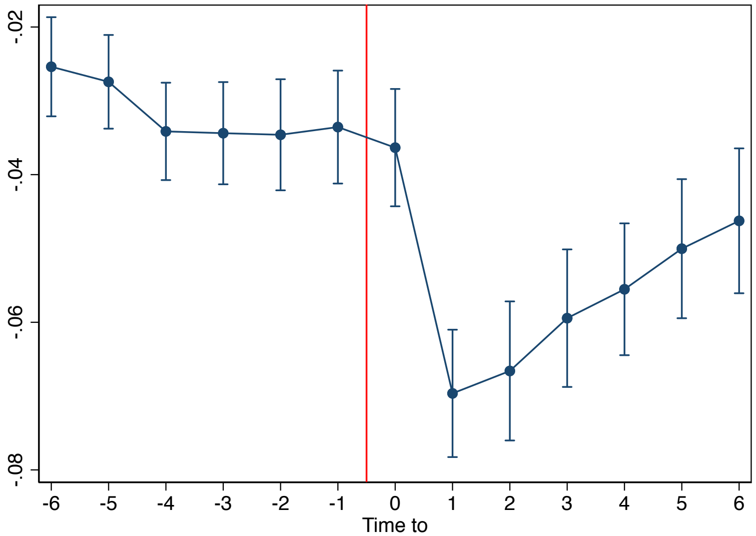
Figure A3: GTD Events and Reporting Activity: Noisy level effect on number of articles around violent events



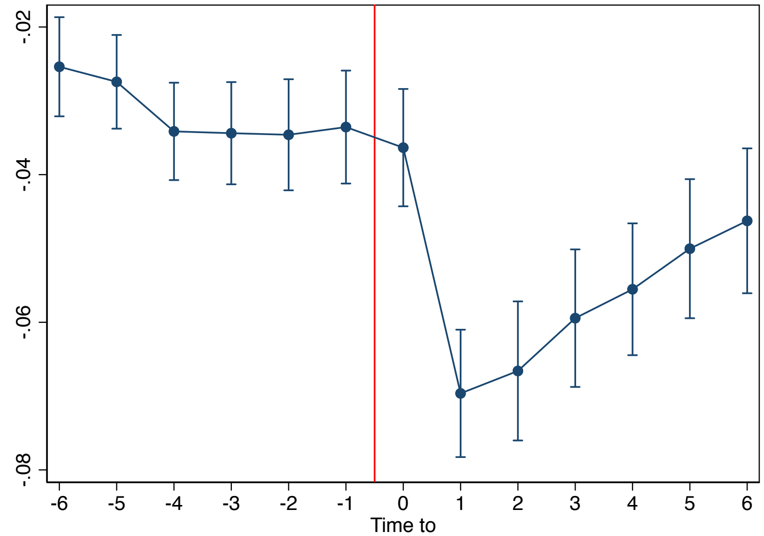
Notes: Figure plots point estimates from a regression that absorbs event, reporting dyad and day fixed effects. The plotted point estimates capture the timing of reporting on a dyad specific to the timing of an individual event recorded in the GTD dataset. 90% confidence intervals obtained from clustering standard errors at the dyad level are indicated.

Figure A4: Event study evidence of the average effect of violent events on tourist activity

Panel A: log(Spending)

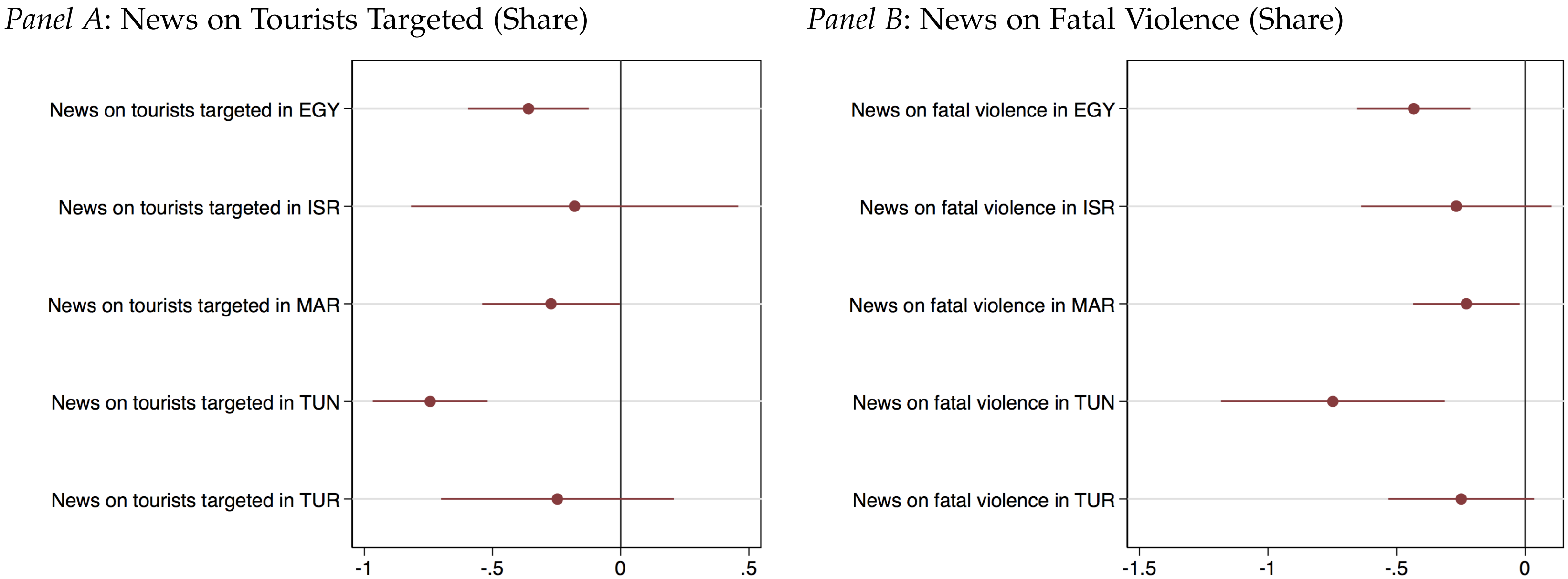


Panel B: log(Cards)



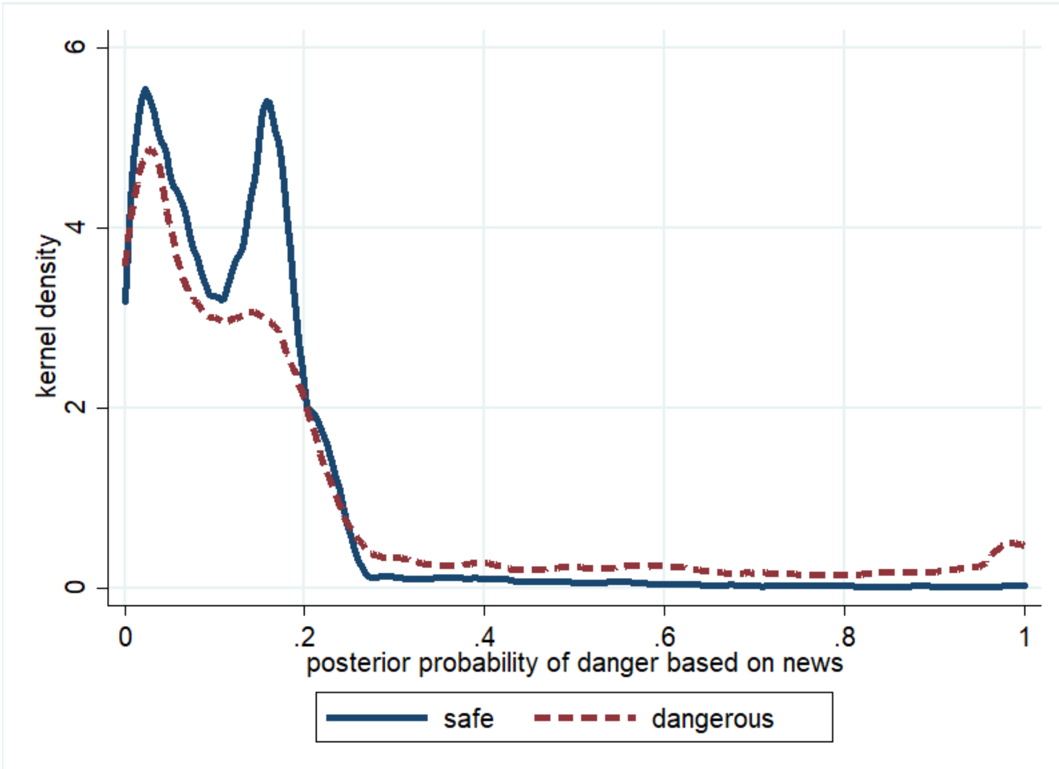
Notes: Figure plots results from an event study design exploring the effect of time series variation in the share of (any) fatal violence or on violence directed towards tourists across four main countries.

Figure A5: Heterogeneity of the Effect of News reporting on Aggregated Spending by Card Issuing Country



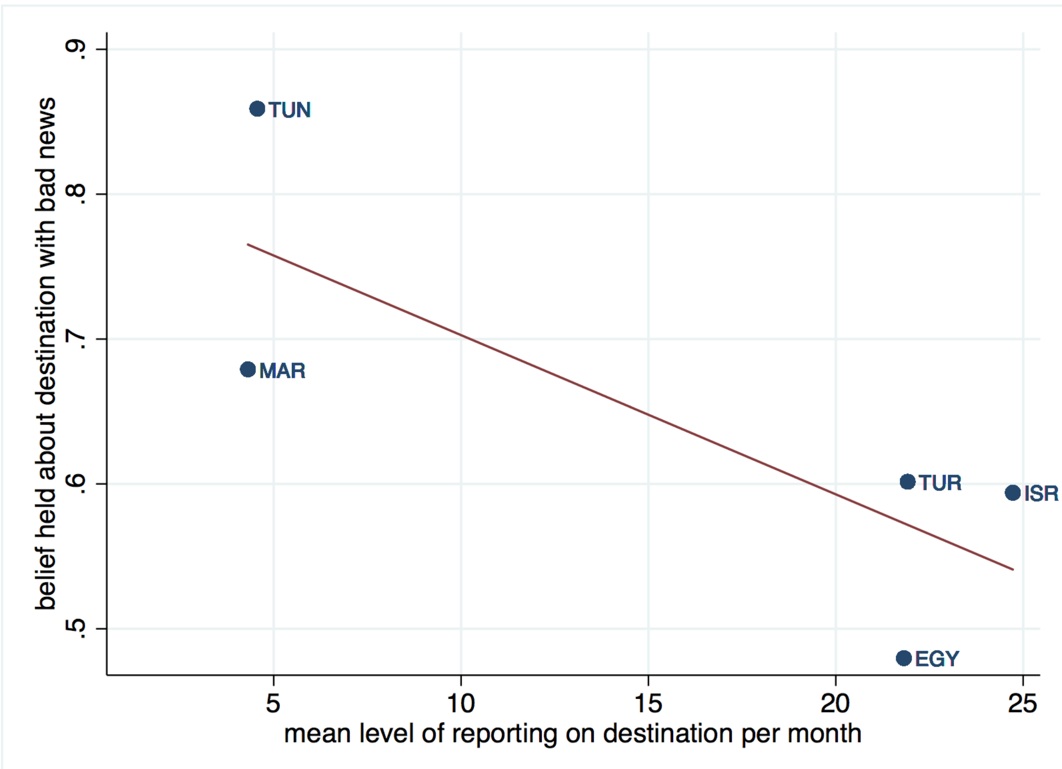
Notes: Figure plots point estimates from a regression that absorbs dyad, issuing-country by time fixed effects and destination by month fixed effects. 90% confidence intervals obtained from clustering standard errors at the dyad level are indicated.

Figure A6: Distribution of Beliefs about Safety or Danger



Notes: Figure plots the distribution of the posterior beliefs about a destination being safe or dangerous held by tourists from different origin countries.

Figure A7: Evidence on the correlation between the level of news reporting and average beliefs about violence in months with violent events



Notes: Figure highlights the interactive relationship between the mean-level reporting on the x-axis about a destination country and the estimated belief about the state of the world being dangerous conditional on there being bad news (violence with fatalities or targeted at tourists) on the y-axis . The figure highlights that lower levels of mean reporting are associated with higher levels of beliefs about the underlying state of the world indicating danger.

Table A1: Validation of aggregate spending data and official annual dyadic tourist arrival data available from UNWTO for a small subset of countries

	Accounts (1)	Transactions (2)	Spend (3)
Panel A:			
arrivals	0.700***	1.189***	182.604***
	(0.197)	(0.262)	(60.961)
Dyads	294	294	294
Observations	1258	1258	1258
Panel B:			
arrivals	0.535***	1.048***	126.985***
	(0.097)	(0.190)	(39.719)
L.arrivals	-0.016	-0.021	0.271
	(0.067)	(0.108)	(20.866)
Dyads	290	290	290
Observations	974	974	974
Panel C:			
F.arrivals	0.344**	0.619**	83.950***
	(0.149)	(0.256)	(31.125)
arrivals	0.755***	1.183***	204.813***
	(0.206)	(0.299)	(62.734)
Dyads	286	286	286
Observations	961	961	961
Dyad FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: Robust standard errors clustered at destination by time level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Explanatory variables are lagged by one month to account for the lagged response of tourism to events. We also divide all explanatory variables by their standard deviation so that the coefficients can be interpreted as the response of spending to one standard deviation increase in violence regardless of the violence measure. Components are coming from principal component analysis of all different violence data sub-categories.

Table A2: Event Characteristics and Reporting Intensity *across dyads*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Share of articles indicating fatal violence					Share of articles indicating tourist targeted				
post	0.002***	0.002***	0.002***	0.011***	0.003*	-0.000	0.000***	0.000**	0.001**	-0.005***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
post × Casualties	0.000***				0.002***	0.000***				0.002***
	(0.000)				(0.000)	(0.000)				(0.000)
post × US Casualties		0.014***			0.016**		0.001**			0.001**
		(0.002)			(0.007)		(0.001)			(0.001)
post × Suicide attack			0.017***		0.020***			0.002***		-0.002
			(0.002)		(0.006)			(0.000)		(0.004)
post × Tourist targeted				0.014***	0.008***				0.022***	0.016***
				(0.003)	(0.003)				(0.003)	(0.002)
Observations	6033450	6122712	6122712	57855	57855	6033450	6122712	6122712	57855	57855
Number of Events										
Dyad FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Event FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at destination/month level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Explanatory variables are lagged by one month to account for the lagged response of tourism to events and news. Event controls are the first four principal components of the eight violence measures from Table 2, column (5).

Table A3: Principal component-based violence measures and effect on aggregate spending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	log(Spending)					log(Cards)				
Armed violence component 1	-0.081***			-0.067***	-0.086***	-0.068***			-0.053***	-0.065***
	(0.017)			(0.017)	(0.017)	(0.016)			(0.017)	(0.019)
Armed violence component 2		-0.043*		-0.040***	-0.029**		-0.034		-0.034**	-0.032**
		(0.025)		(0.014)	(0.014)		(0.021)		(0.015)	(0.016)
Armed violence component 3			0.021	0.017	0.011			0.013	0.010	0.008
			(0.014)	(0.015)	(0.014)			(0.013)	(0.015)	(0.016)
Armed violence component 4				-0.031**	-0.015				-0.039***	-0.032**
				(0.013)	(0.014)				(0.014)	(0.015)
Observations	42254	42254	42254	42254	23859	42299	42299	42299	42299	23869
R2	.947	.947	.947	.947	.966	.97	.969	.969	.97	.971
Dyad FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Origin/Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Dest./Month FE	YES	YES	YES	YES	NO	YES	YES	YES	YES	NO
Dest. x Time FE	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES

Notes: Robust standard errors clustered at destination by time level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Explanatory variables are lagged by one month to account for the lagged response of tourism to events. We also divide all explanatory variables by their standard deviation so that the coefficients can be interpreted as the response of spending to one standard deviation increase in violence regardless of the violence measure. Components are coming from principal component analysis of all different violence data sub-categories.

Table A4: Robustness of Effect of Violence and Aggregate Spending: Dropping each country in turn

	(1)	(2)	(3)	(4)	(5)	(6)
		Dropping a country in turn				
	All	EGY	TUN	TUR	MAR	ISR
Panel A:						
Armed violence component 1	-0.081***	-0.041***	-0.094***	-0.114***	-0.067***	-0.095***
	(0.008)	(0.010)	(0.008)	(0.010)	(0.008)	(0.013)
Observations	42268	33315	35610	32617	34241	32851
R2	.947	.954	.95	.945	.952	.953
Panel B:						
GTD Events	-0.076***	-0.030***	-0.089***	-0.110***	-0.063***	-0.085***
	(0.008)	(0.010)	(0.008)	(0.010)	(0.008)	(0.012)
Observations	42254	33315	35596	32600	34227	32834
R2	.947	.954	.95	.945	.952	.953
Panel C:						
ICEWS armed violence events	-0.068***	-0.025**	-0.081***	-0.118***	-0.056***	-0.070***
	(0.008)	(0.010)	(0.008)	(0.010)	(0.008)	(0.010)
Observations	42254	33315	35596	32600	34227	32834
R2	.947	.954	.95	.945	.952	.953
Panel D:						
UCDP Events	-0.040***	-0.034***	-0.043***	-0.042***	-0.039***	-0.045***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.016)
Observations	42254	33315	35596	32600	34227	32834
R2	.947	.954	.95	.944	.952	.953
Dest./Month FE	YES	YES	YES	YES	YES	YES
Origin/Time FE	YES	YES	YES	YES	YES	YES
Dyad FE	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at destination by time level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Explanatory variables are lagged by one month to account for the lagged response of tourism to events. We also divide all explanatory variables by their standard deviation so that the coefficients can be interpreted as the response of spending to one standard deviation increase in violence regardless of the violence measure. Components are coming from principal component analysis of all different violence data sub-categories.

Table A5: Relationship between Reporting and Aggregate Spending

	(1)	(2)	(3)	(4)
		log(Spending)		
News on tourists targeted (count of articles)	-0.006**	-0.002		
	(0.002)	(0.002)		
News on tourists targeted (share of all articles)	-0.494***	-0.199**		
	(0.101)	(0.091)		
Armed violence component 1	-0.084***		-0.084***	
	(0.009)		(0.009)	
Armed violence component 2	-0.026***		-0.028***	
	(0.006)		(0.006)	
Armed violence component 3	0.018***		0.013***	
	(0.004)		(0.004)	
Armed violence component 4	-0.015*		-0.016*	
	(0.009)		(0.009)	
Violent events with fatalities (count of articles)			0.001	0.003
			(0.003)	(0.003)
News on violence with fatalities (share of all articles)			-0.351***	-0.222**
			(0.102)	(0.096)
Observations	23859	23859	23859	23859
R2	.967	.972	.967	.972
Dyad FE	YES	YES	YES	YES
Origin/Time FE	YES	YES	YES	YES
Dest./Month FE	YES	NO	YES	NO
Event controls	YES	NO	YES	NO
Dest./Time FE	NO	YES	NO	YES

Notes: Robust standard errors clustered at destination/month level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Explanatory variables are lagged by one month to account for the lagged response of tourism to events and news. Event controls are the first four principal components of the eight violence measures from Table **??**, column (6).

Table A6: Robustness to additional control variables and different violent news coding cutoffs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Additional controls				Alternative classification cutoffs & not relying on hand coding					
					$c = 0.5$		$precision = 0.90$		$precision = 0.95$	
Panel A: News on tourist being targeted										
News on tourists targeted (share of all articles)	-0.529***	-0.559***	-0.205**	-0.153*	-0.286***	-0.102**	-0.852***	-0.327**	-0.963***	-0.303
	(0.098)	(0.097)	(0.090)	(0.080)	(0.045)	(0.044)	(0.168)	(0.143)	(0.257)	(0.203)
Observations	23859	23859	23859	23859	23859	23859	23859	23859	23859	23859
R2	.967	.967	.972	.976	.967	.972	.967	.972	.967	.972
Panel B: News on any fatal violence										
News on violence with fatalities (count of articles)	-0.337***	-0.380***	-0.196**	-0.199**	-0.167***	-0.085**	-0.337***	-0.196**	-0.244***	-0.073
	(0.098)	(0.098)	(0.093)	(0.080)	(0.040)	(0.035)	(0.098)	(0.093)	(0.082)	(0.078)
Observations	23859	23859	23859	23859	23859	23859	23859	23859	23859	23859
R2	.967	.967	.972	.976	.967	.972	.967	.972	.966	.972
Dyad FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Origin by Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Destination by Month FE	YES	YES	NO	NO	YES	NO	YES	NO	YES	NO
Destination by Time FE	NO	NO	YES	YES	NO	YES	NO	YES	NO	YES
Dyad Linear Trend	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO
Exchange rate	NO	YES	NO	NO	NO	NO	NO	NO	NO	NO

Notes: Robust standard errors clustered at destination by time level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Explanatory variables are lagged by one month to account for the lagged response of tourism to events. We employ two alternative classification cutoffs c as discussed in section. In columns (5) - (10) we rely on the news measures constructed not using the secondary hand coding procedure we described in . The columns explore alternative classification cutoffs to highlight results are robust. All explanatory variables by their standard deviation so that the coefficients can be interpreted as the response of aggregate spending to one standard deviation increase in violence regardless of the violence measure.

Table A7: Markov Chain Estimates of Parameters

	hrid EGY	TUN	TUR	ISR	MAR
mean violence in danger	0.46	0.300	0.50	0.431	0.27
mean violence in safety	0.31	0.270	0.30	0.309	0.27
difference (danger-safety)	0.14	0.030	0.20	0.122	0.00
persistence of danger	0.96	0.601	0.93	0.814	0.27
persistence of safety	0.99	0.856	0.97	0.929	0.84

Notes: Table reports estimates of the markov chain switching model parameters.

Table A8: Effect of Markov Chain Fitted Probability of Dangerous State on Spending across destination countries

probability of danger (news-based) in Egypt	-0.951***
	(0.092)
probability of danger (news-based) in Israel	-0.508***
	(0.166)
probability of danger (news-based) in Morocco	-0.214
	(0.207)
probability of danger (news-based) in Tunisia	-1.065***
	(0.185)
probability of danger (news-based) in Turkey	-0.524***
	(0.095)
Observations	23859
R2	.967

Notes: All regressions include dyad, destination by month and origin country by time fixed effects. Robust standard errors clustered at the dyad level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Explanatory variables are lagged by one month to account for the lagged response of tourism to events. The dependent variable is the log of spending.

D Description of Machine Learning Method and Validation

We developed the algorithm for spotting fatal violence and attacks on tourists to identify articles out of sample. Training was always conducted on a balanced set, i.e. 1:1 negatives and positives, but we knew that the final dataset would be very imbalanced. This was a particularly important concern for attacks against tourists which is why we checked the coding results by hand for these news.

In all applications we exclude tokens that appear in less than 100 articles. We sometimes improved the fit with choosing a higher cutoff of around 150 articles but we also wanted to use an additional method of dimension reduction, the singular value decomposition (SVD), so that we chose 100 as a default. We looked at unigrams, up to bigrams and up to trigrams and experimented extensively with them. Generally, up to trigrams performed clearly the best and we therefor stuck to them.

We use three ways to classify the two news items. First, we use a random forest of depth 12 for fatal violence and depth 9 for attacks against tourists. Second, we use a random forest of the same depth but only after running the SVD. In addition, we use a naive bayes classifier. All steps and hyperparameters were checked using cross validation. A worry we had was that headlines would repeat similar key words so that cross validation used a relatively small training sample (three folds). Figure B1 illustrates the grid-search for the optimal tree depth for attacks against tourists without the SVD, for example. We kept increasing the maximum tree depth and recalculated the AUC on the testing sample of three folds. The Figure illustrates quite nicely how the AUC first rises significantly but then stagnates and falls with rising depth. In order to maintain out-of-sample performance we picked a relatively general tree depth of 9. The higher tree depth of 12 for fatal violence reflects the fact that we have many more circumstances of fatal violence and an algorithm that is able to pick it up a lot better.

Figure B2 shows the performance of the three models, two random forest models and one NB model, on three different folds and on two different samples with sampling rate of 1:1 and 1:10. The y-axis shows the AUC and the x-axis the average precision the respective classifier reached in the sample. The green dots show the result of the ensemble classifier, the simple average of the other three scores. Three things are clear from this. First, the NB performs a lot worse than the random forest - both in terms of AUC and precision. Second, the ensemble is performing better than the random forest, despite the fact that it uses the NB. Thirdly, the precision of the ensemble is less affected by the imbalance and therefore a lot more stable across the different samples. This is an important reason for us to adopt the ensemble method.

Figure B3 shows the precision recall curve for fatal violence on three random folds and Figure B4 shows the same curve for violence against tourists. These figures are particularly important in a context with imbalanced data in which we are worried about precision. ”Recall” on the x-axis is the true positive rate, i.e. the share of all actual articles with violence which the algorithm picks up. ”Precision” on the y-axis is the rate at which articles which were identified as articles with violence actually were articles with violence. Clearly, precision is a lot lower when trying to identify violence against tourists. While the average precision is close to 0.85 for fatal violence it is between 0.59 and 0.71 for violence against tourists. This implies that our precision cut-offs of 90 percent will exclude a lot more articles when we try to identify violence against tourists.

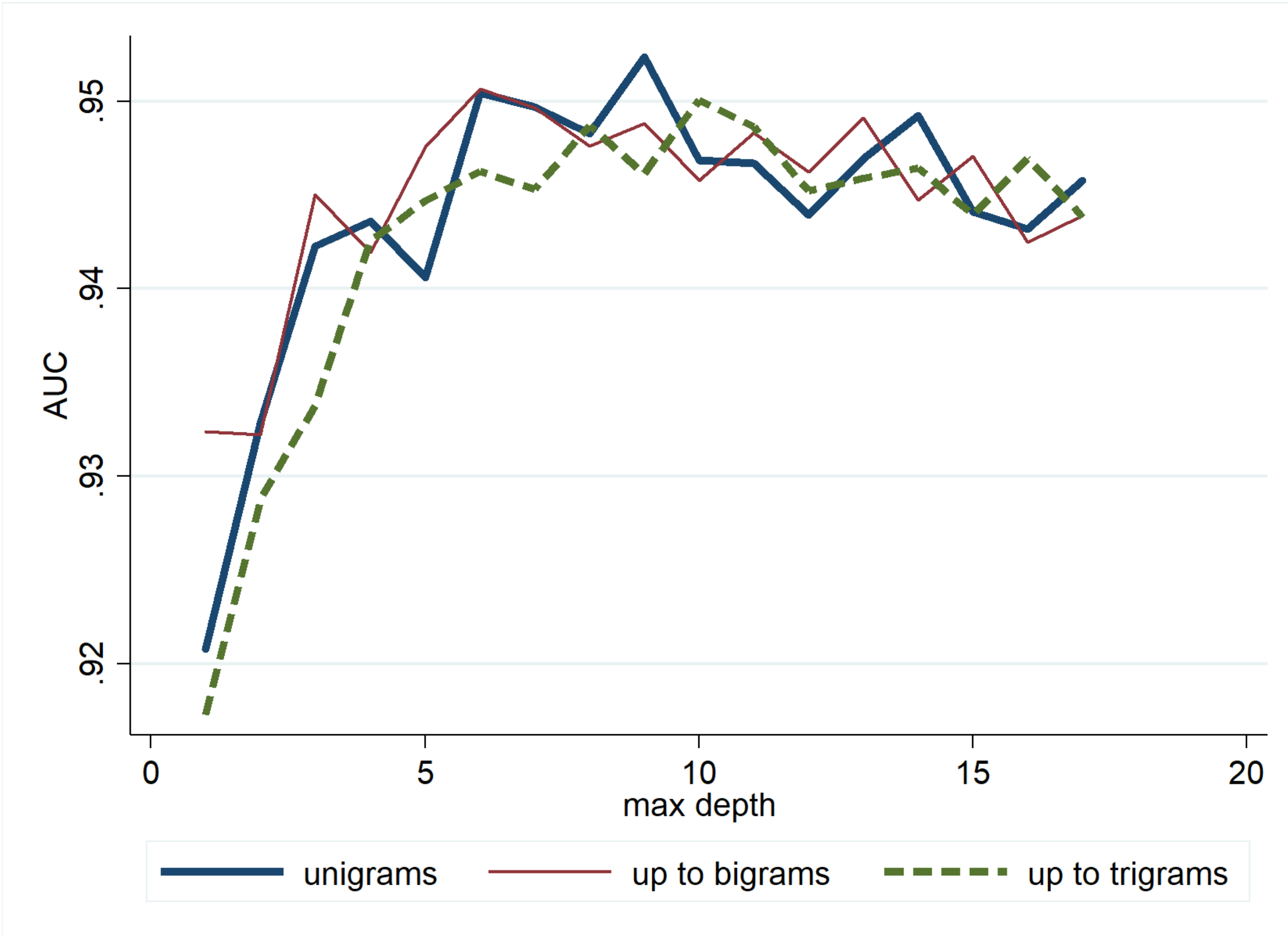
This is why we added an additional layer of hand-coding for violence against tourists. The analysis of mistakes made by the algorithm reveals something interesting about the task of spotting violence against tourists in newspaper articles. Some of these mistakes were difficult judgement calls such as news on shark attacks (on tourists) or an attack on a military bus in Egypt in which no tourists died. Some other manual recodings were driven by the text we downloaded, for example, declarations by our destination countries about events in other countries or when citizens of our destination countries conducted attacks elsewhere. These were downloaded as events in the destination countries and identified by the algorithm as being about tourists being attacked. Most remaining mistakes were driven by reactions to attacks, such as governments investigating the attackers, tourists fleeing the attack or reports about the court cases. We kept many of these codings if they were in the direct aftermath of an attack but excluded them if they were news reports on actions that were not taken in the direct context of an attack.

We also used the hand-coding to get an impression of the error rate that we imposed through our cutoffs. Between the cutoffs of $c = 0.8$ and $c = 0.75$ we hand-code 626 negatives and 192 positives, i.e. the proportions change considerably compared to the sample above $c = 0.8$. Also we find a rapidly declining rate of false negatives in the remaining recodings. In 4,000 additional observations below $c = 0.75$ we found only an additional 416 positives. This is a rate decline of positives per article of 0.904 to 0.235 and 0.104 so that we suspect that the remaining articles will not contain a lot of actual positives. The resulting distribution of coded attacks is displayed in Figure B5 which shows two kernel densities. The first kernel density displays the overall distribution of predictions for violence against tourists coming out of the ensemble. Clearly, the predictions indicate that attacks against tourists is a rare event with most mass at low predictions. The red curve then shows the distribution of probabilities for the articles we identified through the hand coding. This provides a good confirmation of the decreased rate at which positives could be in the sample.[1]

The final proof that the algorithm works comes from a feature of the downloading process. We hand-coded only on articles downloaded from Lexis Nexis but, as we realized the method would work, later downloaded twice as much articles from different countries from Faktiva. In the sample that we confirmed by hand the algorithm had spotted 535 attacks against tourists in the Lexis Nexis sample and 1,052 attacks against tourists in the Faktiva sample. This is a true out-of sample test which implies that we have managed to develop a automated detection of attacks on tourists from the news.

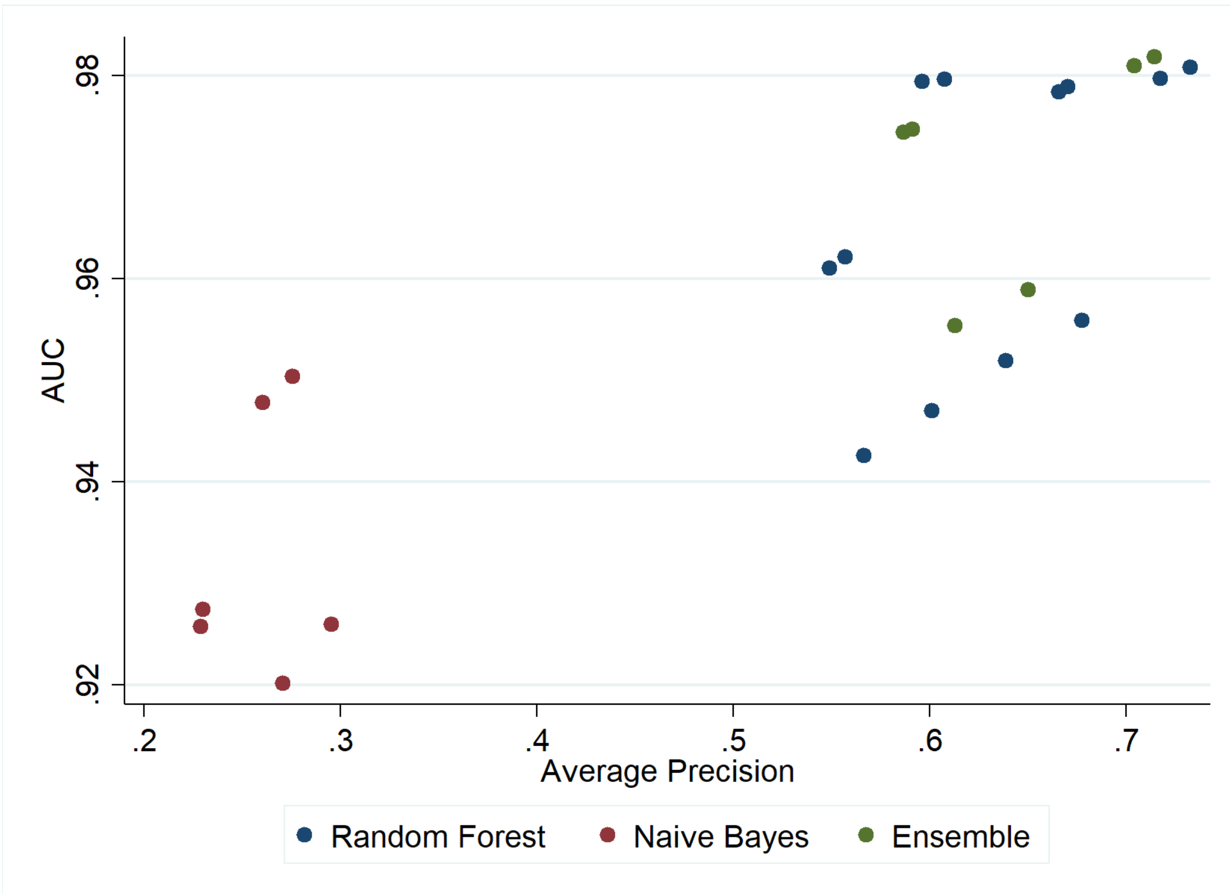
[1] The few positives for low scores were identified from sources with very few articles as our RA sampled the 100 top articles from all sources.

Figure B1: Bias-variance trade-off in search for random forest tree depth



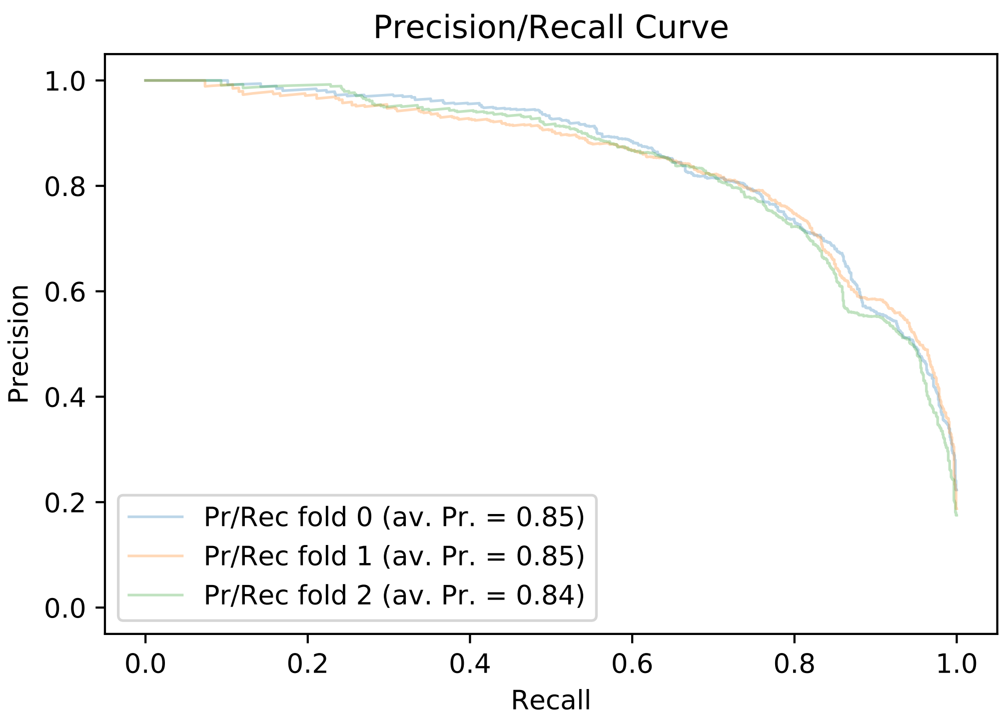
Notes: Figure plots out the AUC curve obtained on the testing sample. For each different maximum tree depth, the AUC is recalculated the three folds. The figure highlights the bias-variance trade-off as the AUC first rises as models are allowed to become more flexible but then stagnates and starts falling as models become too flexible and start overfitting the training data, resulting in worse accuracy in the testing samples.

Figure B2: AUC and Precision across a set of different models



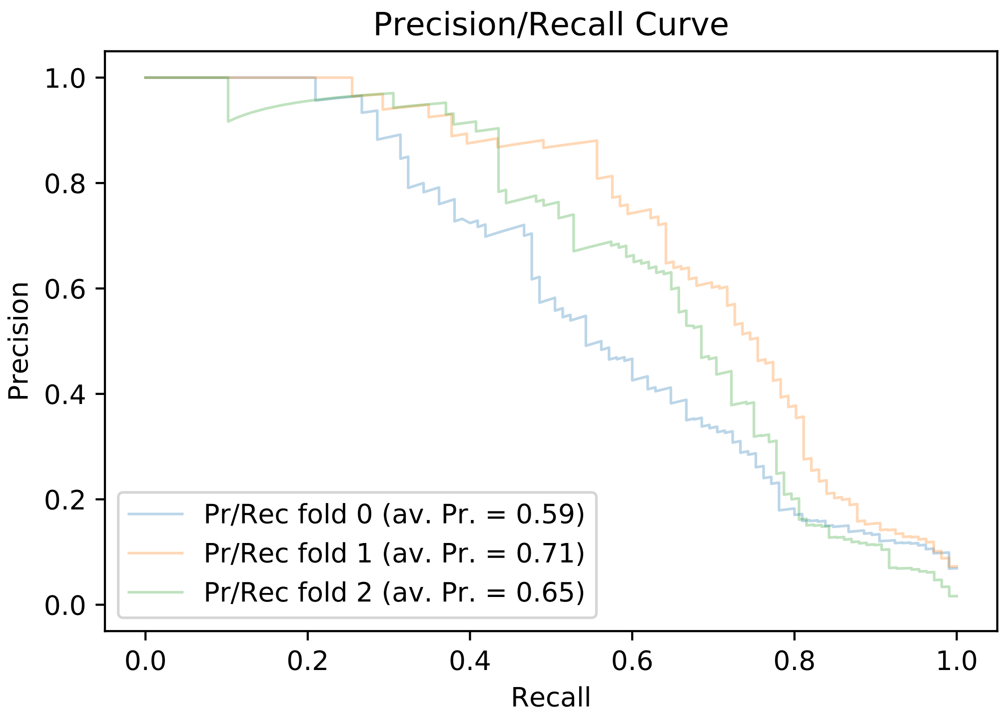
Notes: Figure plots the AUC and precision measured obtained on different folds of data highlighting that Naive Bayes performs worse compared to Random Forests, but that the ensemble of models outperforms the two. Precision of the algorithm captures the share of all correctly classified articles indicating violent events with fatalities among all articles that the algorithm classifies as indicating violence with fatalities.

Figure B3: Classification of articles capturing fatal violence: precision and recall across folds



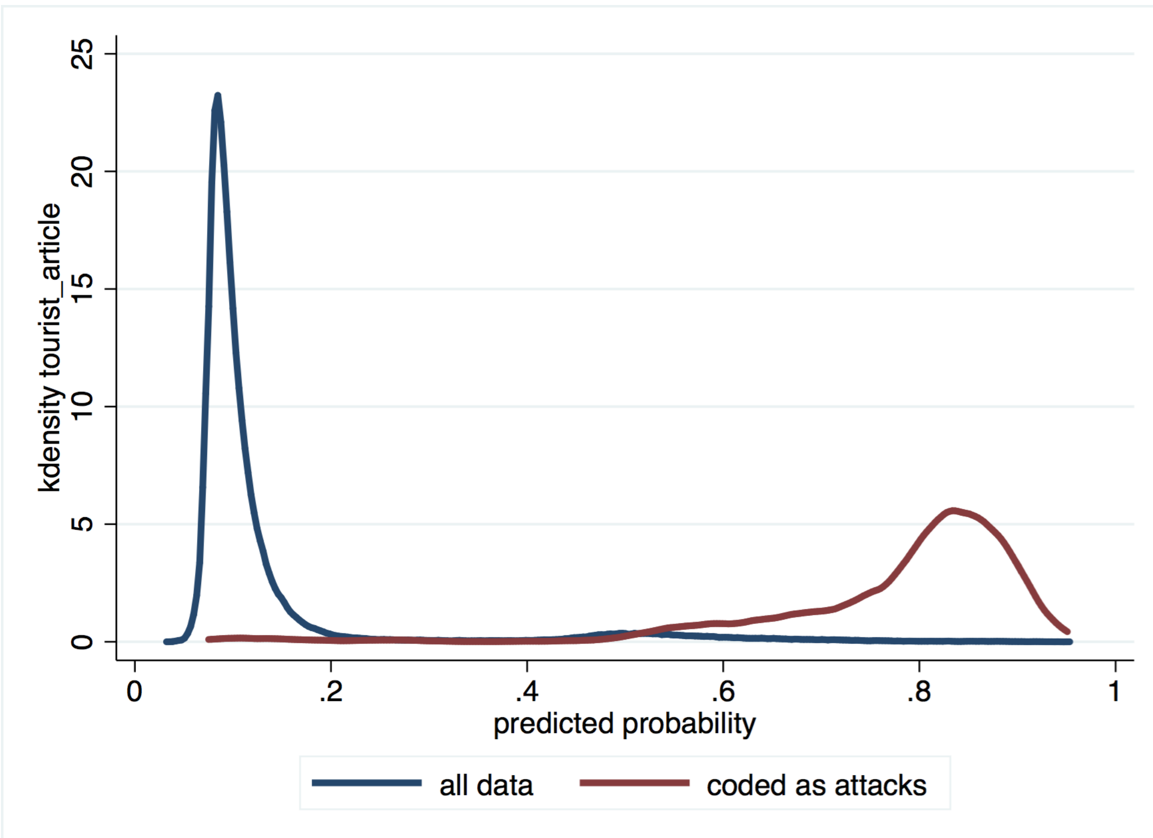
Notes: Figure plots recall on the x-axis. Recall is the true positive rate capturing the share of all actual articles with violence that are correctly picked up by the algorithm picks up AUC. The vertical axis plots out precision, which is the share of all correctly classified articles indicating any violent events with fatalities among all articles that the algorithm classifies as indicating any violent events with fatalities.

Figure B4: Classification of articles capturing violence against tourists: precision and recall across folds



Notes: Figure plots recall on the x-axis. Recall is the true positive rate capturing the share of all actual articles with violence that are correctly picked up by the algorithm picks up AUC. The vertical axis plots out precision, which is the share of all correctly classified articles indicating violence against tourists among all articles that the algorithm classifies as indicating violence against tourists.

Figure B5: Predicted conditional probabilities of class labels after computing ensemble: clear separation of data is achieved



Notes: Figure displays the kernel densities associated with the empirical distributions of the predicted class labels after the ensemble. The data are clearly separated between the two classes.

Table B1: Newspaper coverage sample and sources included

Country	Main Source Name	Article count	Language	Main Source	Flag
ARE	Gulf News	4712	arabic	LexisNexis	
ARG	Source: La Nación (Argentina, Spanish Language)	822	spanish	Factiva	
AUS	Syndey Morning Herald	4492	english	LexisNexis	
AUT	Der Standard	5901	german	Factiva	
BEL	Agentschap Belga (Belgium, Dutch Language)	2140	dutch	Factiva	
BHR	Akhbar Al Khaleej.com (Bahrain, Arabic Language)	20243	arabic	Factiva	agency
BRA	O Globo	3534	portuguese	LexisNexis	
CAN	The Toronto Start	4563	english	LexisNexis	
CHE	Neue Zürcher Zeitung	4427	german	Factiva	
CHL	La Nación (Chile, Spanish Language)	2707	spanish	Factiva	
CHN	Xinhua News Agency	70554	english	LexisNexis	agency
COL	El Tiempo (Colombia, Spanish Language)	593	spanish	Factiva	
CYP	Cyprus Mail	4143	english	Factiva	
CZE	CIA Daily News	920	english	LexisNexis	
DEU	Die Welt	5380	german	Factiva	
DNK	Politiken / Politiken Weekly	6186	danish	LexisNexis	
ESP	El País	29187	spanish	Factiva	
EST	Baltic Business Daily	272	english	Factiva	
FIN	Helsinki Times	736	english	LexisNexis	
FRA	Le Figaro	16072	french	Factiva	
GBR	Daily Telegraph	5755	english	Factiva	
GRC	Athens News Agency	2334	english	Factiva	
HKG	South China Morning Post	855	english	Factiva	
HRV	HINA (Croatia)	723	english	Factiva	
HUN	MTI - EcoNews (Hungary)	736	english	Factiva	
IND	Hindustan Times	3861	english	Factiva	
IRL	The Irish Times	5352	english	Factiva	
ITA	Correrie della Sera	8682	italian	LexisNexis	
JPN	The Tokyo Shimbun	137	japanese	Factiva	
JOR	Addustour (Jordan, Arabic Language)	38402	arabic	Factiva	
KOR	Chosun Ilbo	1129	korean/english	Factiva	
KWT	Kuwait News Agency (Arabic Language)	37195	arabic	LexisNexis	agency
LBN	Tayyar.org (Arabic Language)	10977	arabic	Factiva	
LTU	Lithuanian News Agency - ELTA	969	english	Factiva	
LUX	Tageblatt (Luxembourg, German Language)	2777	german/french	Factiva	
LVA	Vesti Segodnya (Latvia, Russian Language)	793	russian	Factiva	
MEX	Reforma (Mexico, Spanish Language)	1511	spanish	Factiva	
MYS	Berita Dalam Negeri	745	malay	Factiva	
NLD	De Telegraaf	4691	dutch	Factiva	
NZL	The New Zealand Herald	1935	english	LexisNexis	
OMN	Al Shabiba (Oman, Arabic Language)	9201	arabic	Factiva	
PHL	Manila Bulletin (Philippines)	1354	english	Factiva	
POL	Gazeta Wyborcza	738	polish	Factiva	
PRT	Jornal de Notícias	1870	portuguese	Factiva	
QAT	Qatar Tribune	446	english	Factiva	
ROM	AGERPRES (Romania)	1212	english	Factiva	agency
RUS	RIA Novosti (Russia, Russian Language)	55008	russian	Factiva	agency
SAU	Arab News	2655	english	Factiva	
SGP	The Straits Times	1395	english	Factiva	
SVK	TASR - Tlacova Agentura Slovenskej Republiky	407	slovak	LexisNexis	
SVN	STA (Slovenia)	757	english	LexisNexis	
THA	The Nation (Thailand)	1352	english	Factiva	
TUR	Dunya (Turkey, Turkish Language)	27786	turkish	Factiva	agency
TWN	Liberty Times (Taiwan, Chinese Language - Traditional)	1180	chinese	Factiva	
UKR	Delo.ua (Ukraine, Russian Language)	2387	russian	Factiva	
USA	New York Times	18783	english	Factiva	
ZAF	Cape Times	2989	english	Factiva	

Notes: Table presents the names of the main newspaper sources used by country in the paper, along with the original source language and the number of articles covered.

Table B2: Example News Headlines coded as covering violence with fatalities

Country	**Year**	**Month**	**Headline**	$\hat{P}_k(Y_i = 1 \mid D_i)]$
TUR	2011	8	One soldier killed in clash with PKK rebels in southern Turkey	0.987
TUR	2012	10	3 police officers killed in clashes with PKK in Turkey	0.987
EGY	2015	2	17 killed in security raids in Egypt's Sinai	0.987
EGY	2014	4	7 extremists killed, 20 injured in Egypt's Sinai raids	0.987
TUR	2016	9	Two soldiers killed in clashes with PKK in SE Turkey	0.986
TUR	2012	8	2 PKK members killed in southeast Turkey	0.986
TUR	2015	8	2 soldiers killed in PKK attack in SE Turkey	0.986
TUR	2016	9	2 soldiers killed in clash with PKK in SE Turkey	0.986
TUR	2012	10	6 PKK members killed in operation in SE Turkey	0.986
TUR	2016	6	6 soldiers killed in PKK attacks in SE Turkey	0.986
TUR	2016	3	4 soldiers killed in PKK bomb attack in SE Turkey	0.986
TUR	2012	10	3 PKK rebels killed in clash in eastern Turkey	0.986
TUR	2012	8	21 killed, 7 wounded in clashes after mine blasts in SE Turkey	0.986
TUR	2012	11	5 PKK rebels killed in military operation in SE Turkey	0.986
TUR	2013	1	One soldier killed in clashes in SE Turkey	0.986
EGY	2013	9	1 soldier killed, 9 injured by militants in Egypt's Sinai	0.986
TUR	2015	10	3 soldiers killed in clashes with PKK in SE Turkey	0.986
EGY	2013	7	3 terrorists killed in car bomb explosion in Egypt's Sinai	0.986
EGY	2014	9	18 extremists killed in security raid in Egypt's Sinai	0.985
TUR	2012	11	5 Turkish soldiers killed in clash with PKK militants	0.985
EGY	2013	7	2 policemen killed by extremists in Egypt's Sinai	0.985
TUR	2012	12	42 PKK militants killed in eastern Turkey	0.985
TUR	2016	4	1 soldier killed in PKK bomb attack in SE Turkey	0.985
EGY	2015	9	2 killed in suicide car bombing in Egypt's Sinai	0.985
EGY	2013	9	Several militants killed in military raid in Egypt's Sinai: security source	0.985
TUR	2016	4	2 soldiers killed in PKK bomb attack in SE Turkey	0.985
EGY	2013	9	Urgent: Several militants killed in military raid in Egypt's Sinai: security sou	0.985
EGY	2015	2	15 extremists killed in security raid in Egypt's Sinai	0.985
TUR	2012	7	1 Turkish soldier killed, 3 wounded in clashes with PKK	0.985
EGY	2013	8	Urgent: 5 soldiers killed, 8 injured by gunmen in Egypt's Sinai	0.985
EGY	2013	7	Urgent: 2 policemen killed by extremists in Egypt's Sinai	0.985
TUR	2016	3	Update: 4 soldiers, 1 policeman killed in PKK attacks in SE Turkey	0.985
TUR	2010	8	Five PKK rebels killed in clash in southeast Turkey	0.985
EGY	2013	9	9 militants killed in Egypt's Sinai raid: army	0.985
TUR	2012	10	3 soldiers killed in PKK attacks on outposts	0.985
TUR	2011	10	Village guard killed in clash with PKK in southeast Turkey	0.984
TUR	2012	8	4 soldiers killed, 2 wounded in mine blast in SE Turkey	0.984
EGY	2015	10	Police killed in blast in Egypt's Sinai	0.984
EGY	2014	6	8 extremists killed in security raids in Egypt's Sinai	0.984
TUR	2012	7	15 PKK members killed in clashes with troops in southeastern Turkey	0.984
EGY	2013	8	25 policemen killed in attack in Egypt's Sinai: official	0.984
TUR	2016	9	5 soldiers killed, 6 wounded in PKK attack in SE Turkey	0.984
EGY	2013	9	Urgent: 1 soldier killed, 9 injured by militants in Egypt's Sinai	0.984
EGY	2013	7	2 policemen killed by gunmen in Egypt's Sinai	0.984
EGY	2015	7	5 soldiers killed in Egypt's north Sinai in clash with IS branch	0.984
TUR	2012	12	3 PKK members killed in eastern Turkey	0.984
TUR	2011	9	One policeman and wife killed by PKK in eastern Turkey	0.984
TUR	2012	6	Two killed in clashes in southeastern Turkey	0.984
TUR	2016	7	3 police killed in PKK bomb attack in SE Turkey	0.984
TUR	2016	3	26 PKK militants killed in SE Turkey	0.984

Notes: Table presents some example headlines of articles that are classified as being covering violence along with the estimated $\hat{P}_k(Y_i = 1 \mid D_i)]$.

Table B3: Example News Headlines coded as covering violence

Country	**Year**	**Month**	**Headline**	$\hat{P}_k(Y_i = 1 \mid D_i)]$
TUN	2015	3	Spanish couple escapes Tunisia attack by hiding in cupboard for 23 hours	0.948
TUN	2015	6	Kuwait Embassy in Tunisia: no Kuwaiti nat'ls in Tunisia terrorist attack	0.934
TUN	2015	6	Urgent: Armerd men attack Sousse hotel in Tunisia	0.889
TUN	2015	6	Austrian Chancellor's expresses sorrow over Kuwait, Tunisia and France attacks	0.881
TUN	2015	6	Tunisia apprehends culprits behind Sousse resort attack	0.870
TUN	2015	3	1st LD: 19 killed, including 17 tourists, in Tunisia's museum attack: PM	0.865
EGY	2012	2	Three South Korean tourists held by locals in Egypt's Sinai, kidnapper identifie	0.862
TUN	2013	11	Suicide bomber targets top Tunisian tourist destination	0.861
TUN	2016	3	Roundup: Jihadist attacks shiver Tunisia's calm, eliciting casualties	0.857
EGY	2014	2	S. Korea censures terrorist attack on tourist bus in Egypt	0.846
MAR	2011	4	Sarkozy condemns Marrakech attack	0.844
TUN	2015	6	Thousands of European tourists are evacuated from Tunisia	0.835
TUN	2015	3	8 tourists killed in Tunisia museum attack	0.835
TUN	2015	11	A new attack is enraged with the Tunisian transition	0.832
EGY	2014	2	Urgent: Tourist bus explodes in Egypt's Taba, casualties feared	0.828
TUN	2015	6	Thousands of European tourists are evacuated from Tunisia ¡¿	0.826
TUR	2016	6	A suicide attack causes at least 36 deaths at the Istanbul airport	0.825
TUN	2015	3	Slovak gov't sends plane to evacuate Children's Folk Group from Tunisia	0.818
TUR	2016	1	The jihadist attack on the hotel in Burkina causes 23 dead	0.817
EGY	2012	2	Three South Korean tourists held by locals in Egypt's Sinai	0.814
TUN	2015	3	Third French tourist probably killed in Tunis attack: Hollande	0.814
TUR	2016	6	A suicide attack causes at least 28 deaths at the Istanbul airport	0.808
TUN	2015	6	Thousands of visitors are evacuated from Tunisia after the attack	0.806
TUN	2015	3	Two Spanish pensioners die in the attack against the Bardo Museum	0.805
TUN	2015	6	Bloody Friday Jihadism shows its cruelty in the attacks in Tunisia Lyon and Kuwa	0.803
TUN	2015	3	Feature: Italy mourns four victims in Tunisia's museum attack	0.798
TUN	2015	6	Tunisia's transitional priority target of terror	0.794
TUN	2015	3	We thought we were going to die, we've had a terrible time	0.793
TUN	2015	3	Roundup: Tunisia tries to restore national image after deadly museum attack	0.792
TUN	2015	3	Tunisia ... Hostages taken after attack at Bardo museum	0.791
EGY	2012	2	Urgent: Egypt's Bedouins release three South Korean tourists	0.791
TUN	2015	6	Gunman Focused on Tourists in Slaughter at a Tunisian Beach Hotel	0.786
TUN	2015	6	I could hear the bullets whining Gary Pine English tourist on the beach in Souss	0.786
TUN	2015	3	2nd LD: 21 killed, including 17 foreigners, in Tunisia's museum attack: PM	0.783
TUN	2015	3	Militants hold tourists hostages inside Tunisia museum	0.780
TUN	2015	6	Irish woman among fatalities in Tunisia attack	0.762
TUN	2015	6	Scores Die in Attack at Tunisian Beach Hotel	0.758
TUN	2015	6	5th LD: Death toll rises to 37 in catastrophic hotel attack in Tunisia	0.756
TUN	2015	6	Norway condemns attacks in Tunisia, France, Kuwait	0.753
TUN	2015	3	Belgium to open own investigation into Tunisia attacks	0.752
TUN	2015	3	Bardo museum reopens a week after killings; Tunisia sends out message country s	0.744
TUN	2015	6	4th LD: 28 killed, 36 injured in terror attack on Tunisia hotel	0.739
TUN	2015	6	Thousands of visitors are evacuated from Tunisia after the attack ¡¿	0.735
TUN	2015	3	The attack of the Bardo museum in Tunisia .. What do we know about the nationali	0.734
TUN	2015	6	Germany condemns deadly hotel attack in Tunisia	0.732
TUN	2015	6	After Tunisia attack, UK ups Wimbledon security	0.729
TUN	2015	3	Hollande expresses solidarity with Tunisia after deadly attack	0.726
TUN	2015	6	Deaths of British nationals in Friday's attack in Tunisia rise to 15: FCO	0.725
EGY	2012	2	1st LD Egypt's Bedouins release three South Korean tourists	0.717
TUN	2015	6	3rd LD: Terrorist suspect in Tunisia's hotel attack arrested: official	0.711

Notes: Table presents some example headlines of articles that are classified as being covering violence along with the estimated $\hat{P}_k(Y_i = 1 \mid D_i)]$.