EC331 Presentation

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Introduction

Research Objectives

- Aim to estimate asset market responses to terror
  - Both short-term responses in the order of days or weeks.
  - Longer term responses to ‘terror waves’ e.g. Good Friday Agreement, rise of Islamic terror.
- Use a mixture of techniques to identify responses, primarily in a Bayesian setting.
  - Event study.
  - Hierarchical logistic regression.
  - Hierarchical shrinkage models.
- Short term responses are characterised by extreme heterogeneity.
  - Currently struggling to accurately pin this down.
- Long run responses TBC.

Context

- Terrorism seems to have a negative effect on economies.
  - Abadie & Dimisi (2006) look at agglomeration economies of scale.
  - Abadie & Gardeazabal (2003) synthetic controls and ETA.
  - Enders & Sandler (2008) Spanish tourism VAR.
- Brodeur (Forthcoming) uses same dataset to address same question with a US focus.

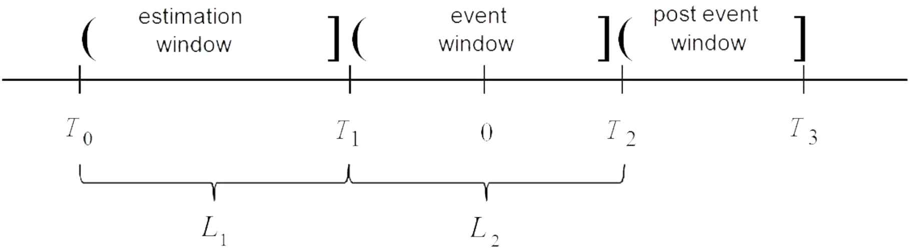
Context II

- There's a large amount of finance literature that explores asset market responses to large attacks.
    - Almost all the current work looks at big events such as the Barcelona bombings, 9/11 and 7/7.
- Tend to find that terror attacks act as a negative shock and banking sector is often most affected, Chesney et al. (2011).
- Not much evidence of firms adjusting terror expectations.
    - A terror shock today is pretty similar to one a decade ago and high intensity/high frequency windows aren't associated with any terror 'fatigue'.
- Zussman & Zussman (2006, 2008) find heterogenous asset market responses depending on type of attack.
    - Killing high ranking politicans causes the market to fall, killing generals causes a positive bump. (In the context of the Israeli-Palestinian conflict)

Methodology

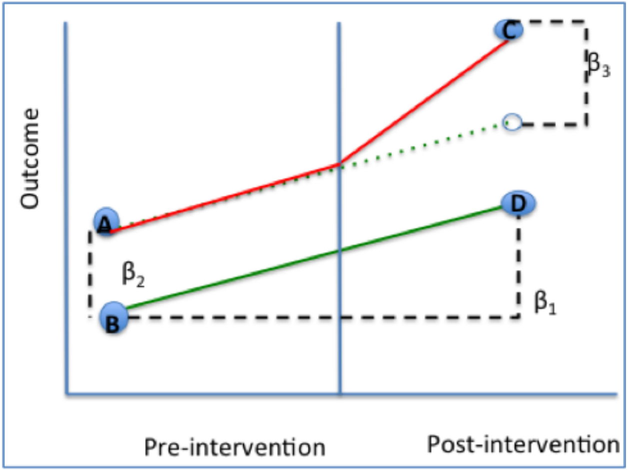
Event Study

Event Study I



- Formulae for cumulative abnormal returns:
  - $AR_{i,\tau} = R_{i,\tau} - E[R_{i,\tau}|\Omega_{i,\tau}]$
  - $CAR_{i(\tau_1,\tau_2)} = \sum_{t=\tau_1}^{\tau_2} AR_{i,t}$
- And then taking an average: $CAAR_{(\tau_1,\tau_2)} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i(\tau_1,\tau_2)}$
- There's a range of different ways of specifying $E[R_{i,\tau}|\Omega_{i,\tau}]$
- But for index data can only use constant mean return model.

Event Study II



Conditional Probability

Conditional Probability Method I

- 'Pioneered' by Chesney, Reshetar and Karaman (CRK) in 2011 and never touched since.
- We have a conditional distribution:

$$\pi(z|x) \equiv P(Z_i \leq z|X_i = x)$$

- Where Z_i are index returns and X_i is a lagged vector of Z_i.
- Let $Y_i = I(Z_i \leq z)$ then $E(Y_i|X_i = x) = \pi(z|x)$.
- Basically a regression of Y_i on X_i will give us the probability, conditional on the value of lagged returns, of observing $Z_i \leq z$.

Conditional Probability Method II

- Applying this to terror attacks:

$$Y_{it} = I(R_{it} \leq r_{i,terror})$$

- where R_{it} are the index returns and $r_{i,terror}$ is the observed event day terror return.
- Our X_{it} variable is equal to $R_{i,t-1} - r_{i,pre\_terror}$, that is, lagged index values minus the return the day before the attack.

Conditional Probability Method III

- In words:
  1. Take an event and calculate the event day return.
  2. For the 200 days preceding the event construct an indicator variable Y_{it} that takes value 1 if returns are lower than the event day return and 0 otherwise.
  3. Our X_{it} variable is found by lagging returns by one day and subtracting the return of the day *before* the event.
  4. Regress Y_{it} on X_{it} and plug in our event day return to obtain a fitted out-of-sample value.
- This fitted value can be thought of as the probability of observing a return on the day of the attack more extreme than the return actually observed.

Conditional Probability Method IV

- CRK decide that an event is abnormal if there's less than a 10% probability of observing something worse than the event day return and extreme if less than 5%.
- The advantages of this method are that it's less susceptible to twiddling/p-hacking than the event study where a range of hyperparameters are set by the researcher.
- CRK use a local polynomial regression to fit the model.
  - *This can be considered a bad idea.*
- I instead use a logistic regression, however I immediately run into a problem.
- Some events are *too* extreme.
  - There is 'separation' where our binary Y variable always equals 0 for some events.

Conditional Probability: A Bayesian Approach

Bayesian Primer

- Bayesian econometrics relies on a researcher specifying his/her beliefs about likely parameter values (a prior) and a likelihood function.
- We observe data y conditional on some parameter(s) θ. Using Bayes' rule:

$$p(\theta|y) = \frac{p(y|\theta)\pi(\theta)}{p(y)}$$

- Where $p(y) = \int p(y|\theta)\pi(\theta)d\theta$.
- Specifying a prior lets us overcome the problem of separation.
  - CRT use divine intervention/ignore the problem/an unpublished manuscript set to rock the econometrics world.

No Pooling

- For each terror attack I estimate a separate logistic regression with 'weak' priors:

$$\alpha \sim N(0,1)$$
$$\beta \sim t(\nu = 3, \mu = 0, \sigma = 2.5)$$

$$y_i \sim N(\alpha + \beta x_i, \epsilon_i)$$

- α is the intercept prior and β the slope prior.
- These are standard logistic weak priors from the literature e.g. Gelman et al. (2008), Ghosh et al. (2015).
  - Ghosh et al. deal specifically with the case of separation in logistic regression.

Complete Pooling

- Combine the data from all terror attacks and estimate $\hat{\beta}$, this potentially helps increase the precision of our results and deal with separation.
- Interpretation becomes a little sketchy.
- All the variation in our fitted conditional probability estimates will only come from variation in event day returns and pre-event day returns.
- Identical priors to the no pooling case.

Hierarchical Model

- Previously I set the distribution parameters of α and β to some fixed constant that seemed reasonable.
- Instead I can give these priors their 'own' priors - hyperpriors.

$$\alpha_e \sim N(\gamma_e, \sigma_\gamma)$$
$$\beta_e \sim t(\nu = 3, \mu_e, \sigma_\mu)$$

$$\gamma_e \sim N(0.5, 0.5), \quad \sigma_\gamma \sim N(1, 5)$$
$$\mu_e \sim N(0, 1), \quad \sigma_\mu \sim N(2.5, 5)$$

$$y_{ie} \sim N(\alpha_e + \beta_e x_{ie}, \sigma_{ye}^2)$$

Hierarchical Model II

- This effectively means we partially pool the data.
- If the events are considered identical and there's no heterogeneity across attacks (our $\sigma_{\gamma,\mu} = 0$) the model is identical to the pooled model - we 'shrink' the estimates towards an overall average effect.
- However, if there is event heterogeneity present, estimates are not shrunk but allowed to vary i.e. shrinkage is inversely proportional to $\sigma_{\gamma,\mu}$.

Hierarchical Model III

- You can think of this as there being some underlying population terror parameter Θ.
- Each terror attack is a random draw from this Θ that we observe.
- Each individual attack gives us slightly different results.
- We're not sure if this is because we're estimating different underlying population parameters or because of noise/unobserved heterogeneity.
- So we measure the variance of our attacks and decide to pool or not-pool based off this.

Hierarchical Model IV

- By specifying hyperpriors for both α and β we have a varying slope and varying intercept model.
  - Traditional fixed effects would be sort of analogous to a varying intercept model.
- Methods like this are often used when we have several separate experiments trying to estimate roughly the same effect.
  - e.g. pooling multiple minimum wage studies to improve our minimum wage estimates or testing the external validity of multiple RCTs answering the same research question.

Data

Terror Data

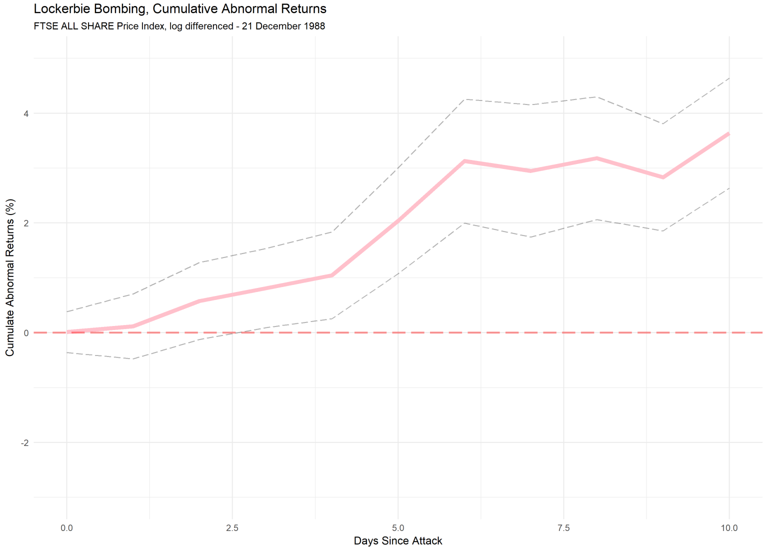
- Using UK terror data from the Global Terrorism Database compiled by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland.
  - Includes a range of variables such as wounded, killed, property damage, target, perpetrator group, ideology and weapon used.
  - Incredibly granular data with information ranging from weapon subtype (was a shotgun, handgun or hands and fists used for instance) to target subtype (was the target a telecommunications facility or military installation)
- There have been 3041 attacks since 1980 in the UK.
- However, when screening for overlapping events this falls to $\sim$100.
- I present results using both a screened and overlapping dataset.
- This is the same dataset used by Brodeur in his forthcoming paper exploring economic costs of terror in US states.

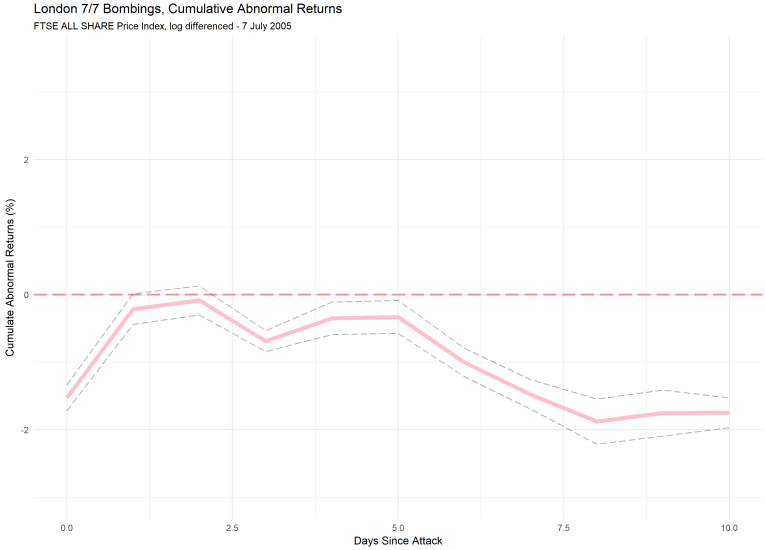
Index Data

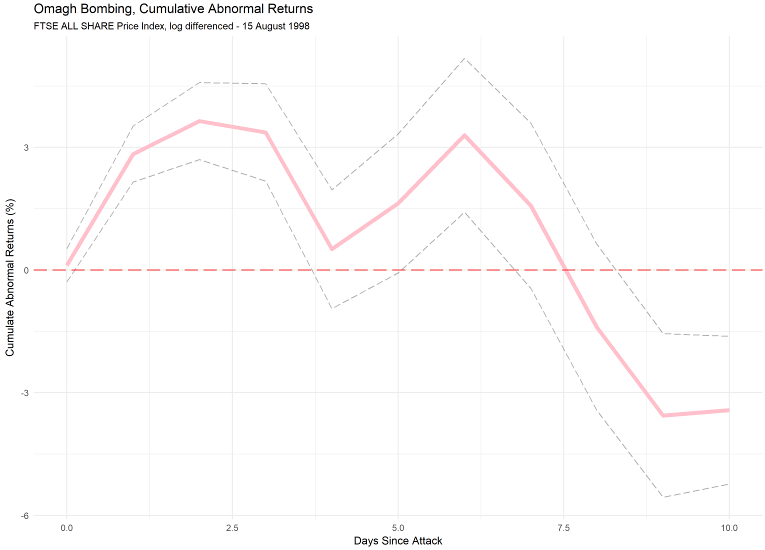
- Daily index return data from Thomson Reuters.
- Results reported using FTSE All-Share unless specified otherwise.
  - Robustness checks performed using a range of alternative indices.
- Financial data is known to have fat tails.
- I use Trapani (2016)'s test for (in)finite fourth moments with a few adaptations and find that I can reject the null of an infinite fourth moment with $p < 10^{-11}$.
- Price data is shown to be non-stationary but transforming to return data (i.e. log-differencing) gives a stationary, I(1), process.

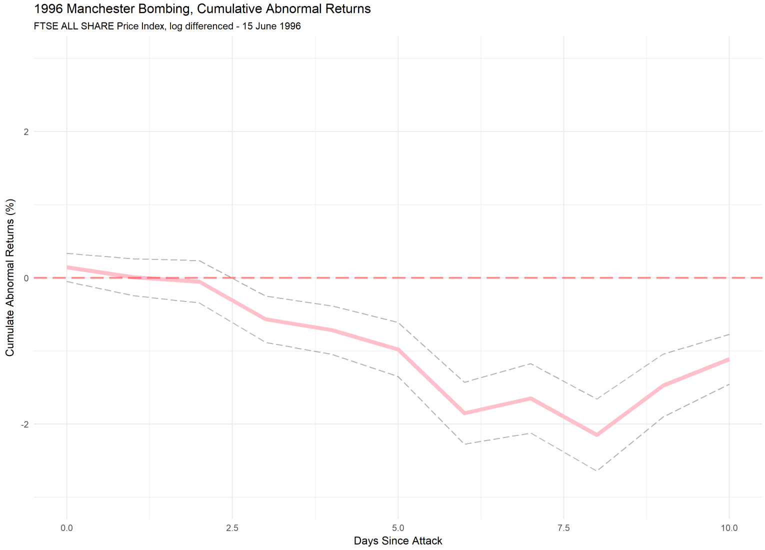
Results I

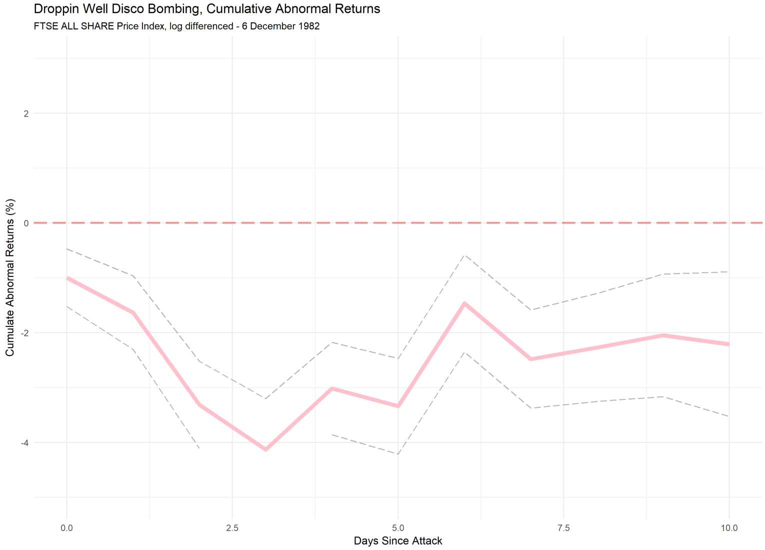
Five Largest Events


Lockerbie Bombing, Cumulative Abnormal Returns
FTSE ALL SHARE Price Index, log differenced - 21 December 1988
Cumulate Abnormal Returns (%)
4
2
0
-2
0.0
2.5
5.0
7.5
10.0
Days Since Attack


London 7/7 Bombings, Cumulative Abnormal Returns
FTSE ALL SHARE Price Index, log differenced - 7 July 2005
Cumulate Abnormal Returns (%)
2
0
-2
0.0
2.5
5.0
7.5
10.0
Days Since Attack

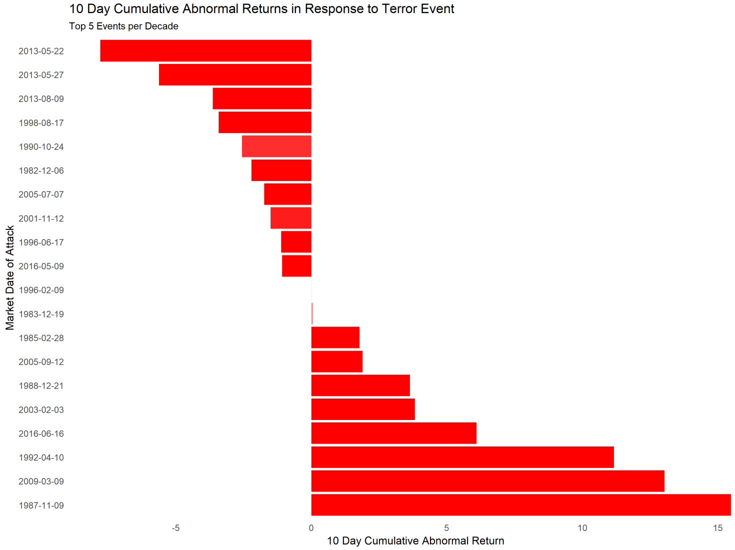

Omagh Bombing, Cumulative Abnormal Returns
FTSE ALL SHARE Price Index, log differenced - 15 August 1998
Cumulate Abnormal Returns (%)
3
0
-3
-6
0.0
2.5
5.0
7.5
10.0
Days Since Attack

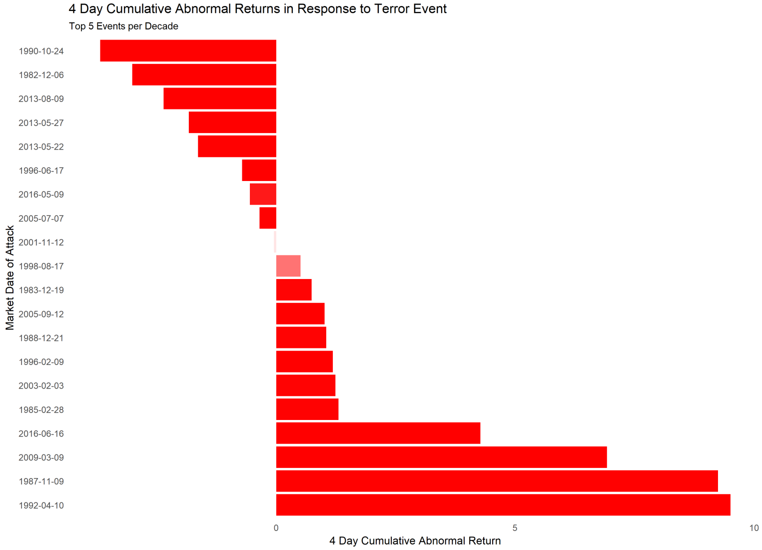

1996 Manchester Bombing, Cumulative Abnormal Returns
FTSE ALL SHARE Price Index, log differenced - 15 June 1996
Cumulate Abnormal Returns (%)
2
0
-2
0.0
2.5
5.0
7.5
10.0
Days Since Attack

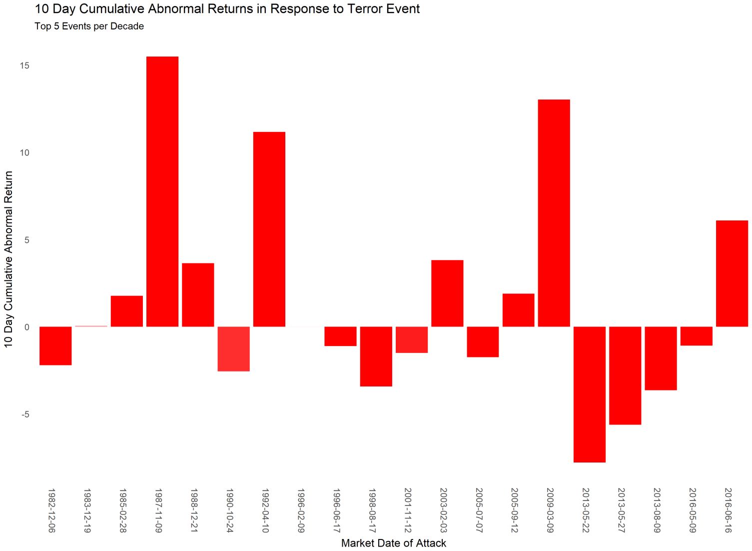


Droppin Well Disco Bombing, Cumulative Abnormal Returns
FTSE ALL SHARE Price Index, log differenced - 6 December 1982
Cumulate Abnormal Returns (%)
2
0
-2
-4
0.0
2.5
5.0
7.5
10.0
Days Since Attack

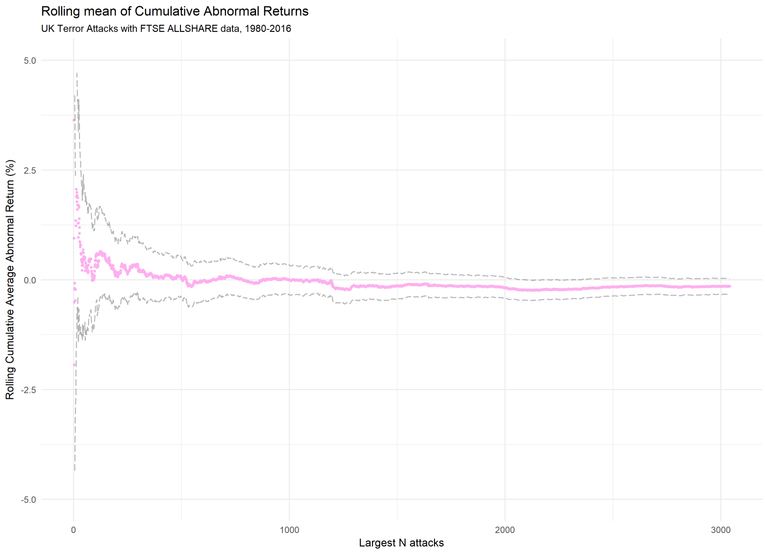
Five Largest Events Per Decade


10 Day Cumulative Abnormal Returns in Response to Terror Event
Top 5 Events per Decade
Market Date of Attack
2013-05-22
2013-05-27
2013-08-09
1998-08-17
1990-10-24
1982-12-06
2005-07-07
2001-11-12
1996-06-17
2016-05-09
1996-02-09
1983-12-19
1985-02-28
2005-09-12
1988-12-21
2003-02-03
2016-06-16
1992-04-10
2009-03-09
1987-11-09
-5
0
5
10
15
10 Day Cumulative Abnormal Return

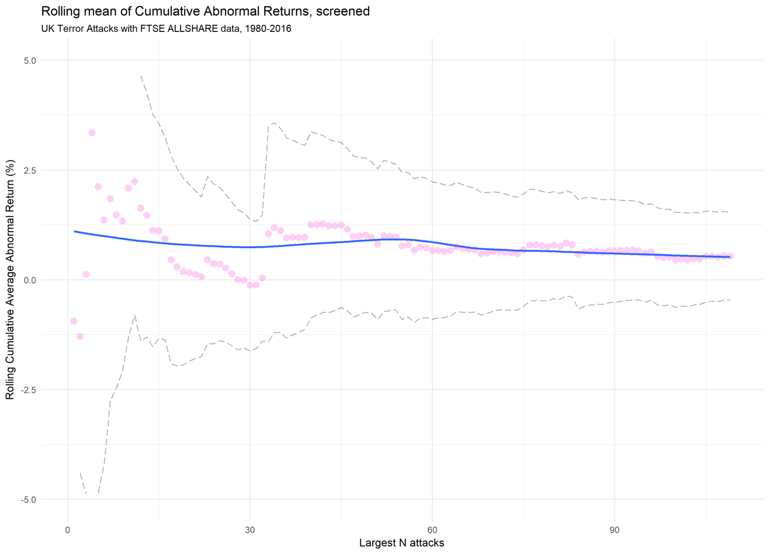

4 Day Cumulative Abnormal Returns in Response to Terror Event
Top 5 Events per Decade
Market Date of Attack
1990-10-24
1982-12-06
2013-08-09
2013-05-27
2013-05-22
1996-06-17
2016-05-09
2005-07-07
2001-11-12
1998-08-17
1983-12-19
2005-09-12
1988-12-21
1996-02-09
2003-02-03
1985-02-28
2016-06-16
2009-03-09
1987-11-09
1992-04-10
0
5
10
4 Day Cumulative Abnormal Return


10 Day Cumulative Abnormal Returns in Response to Terror Event
Top 5 Events per Decade
10 Day Cumulative Abnormal Return
15
10
5
0
-5
1982-12-06
1983-12-19
1985-02-28
1987-11-09
1988-12-21
1990-10-24
1992-04-10
1996-02-09
1996-06-17
1998-08-17
2001-11-12
2003-02-03
2005-07-07
2005-09-12
2009-03-09
2013-05-22
2013-05-27
2013-08-09
2016-05-09
2016-06-16
Market Date of Attack

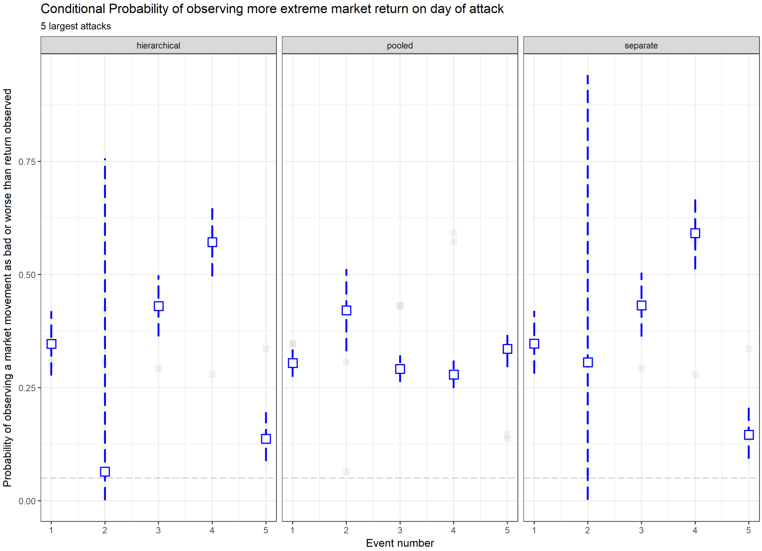
Cumulative Average Abnormal Returns



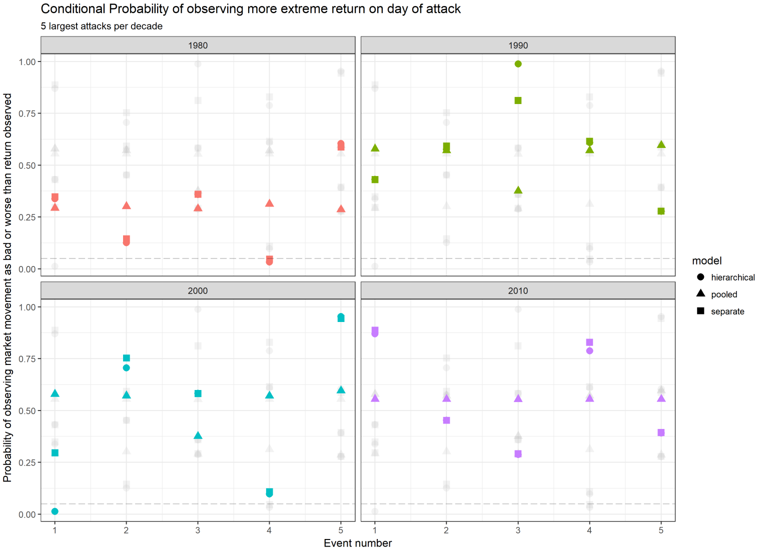
Rolling mean of Cumulative Abnormal Returns
UK Terror Attacks with FTSE ALLSHARE data, 1980-2016
Rolling Cumulative Average Abnormal Return (%)
5.0
2.5
0.0
-2.5
-5.0
0
1000
2000
3000
Largest N attacks

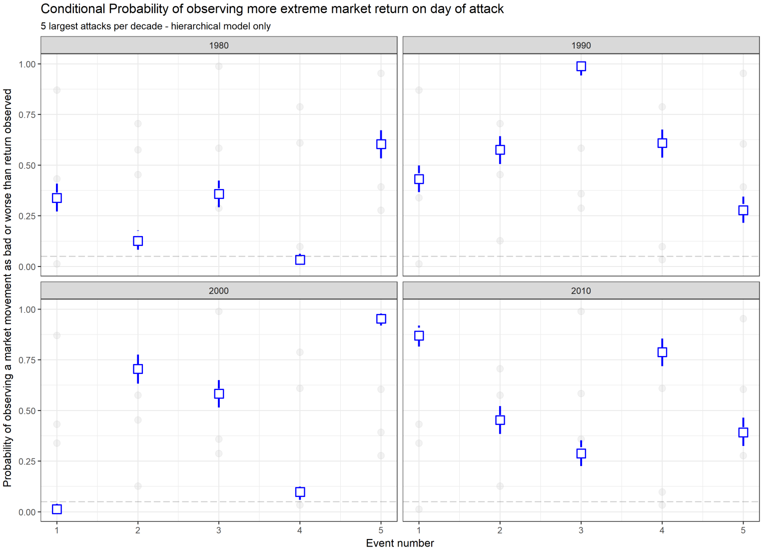

Rolling mean of Cumulative Abnormal Returns, screened
UK Terror Attacks with FTSE ALLSHARE data, 1980-2016
Rolling Cumulative Average Abnormal Return (%)
5.0
2.5
0.0
-2.5
-5.0
0
30
60
90
Largest N attacks

Conditional Probability Results



Conditional Probability of observing more extreme market return on day of attack
5 largest attacks
hierarchical
pooled
separate
Probability of observing a market movement as bad or worse than return observed
0.00
0.25
0.50
0.75
1
2
3
4
5
Event number


Conditional Probability of observing more extreme return on day of attack
5 largest attacks per decade
1980
1990
2000
2010
Probability of observing market movement as bad or worse than return observed
1.00
0.75
0.50
0.25
0.00
Event number
1
2
3
4
5
model
hierarchical
pooled
separate



Conditional Probability of observing more extreme market return on day of attack
5 largest attacks per decade - hierarchical model only
1980
1990
2000
2010
Probability of observing a market movement as bad or worse than return observed
1.00
0.75
0.50
0.25
0.00
1
2
3
4
5
Event number

Brief Summary

- The individual event studies indicate that maybe something is going on here - but it's very tenuous.
- When I aggregate up into CAARs this disappears.
- The conditional probability method seems to come to broadly similar conclusions.
- The hierarchical model offers an improvement over the pooled and separate models but it still only points to 2 extreme events and an additional abnormal event.
- Can we do better by looking at the makeup of terror events in more detail?

Model Extensions

Event Heterogeneity - The ‘No’ Slide

- Can we estimate the determinants of terror responses?
  - Do bombings have greater impacts than shootings?
  - Are lone wolf attacks different to attacks organised by a terror cell?
- Can we find evidence that reconciles the differences between the 5 ‘largest’ attacks and the rest?

Some Issues

- After events have been screened to remove overlap I have ~100 events.
- I have somewhere between 70-100 predictors depending on exact specification used.
- OLS typically doesn't fare too well at estimation under these conditions.
- I need to either increase N or reduce K.
  - Two approaches: relax screening assumptions and/or perform variable selection.

Bayesian LASSO

- Two ways to do this:
  - Estimate traditional OLS with a regularisation parameter and use generic, weak priors (something like N(0,5)).
  - Use a hierarchical shrinkage model with laplace priors on the regression parameters, Park & Casella (2008).

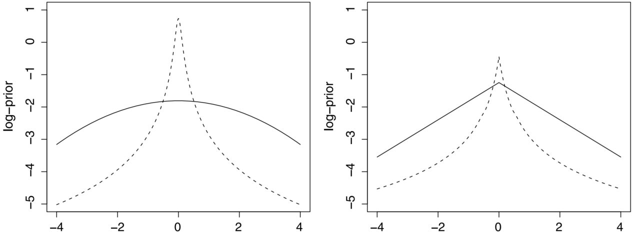


Fig. 1 Conditional (*solid lines*) and marginal (*dashed lines*) log-priors for the ridge (*left panel*) and the lasso prior (*right panel*). Hyperparameters are chosen such that roughly 90% of the probability mass are contained in the interval $[-4, 4]$, leading to $\lambda = 0.57$ for the lasso (if no prior is assigned to λ) and, e.g., $a = 0.08$, $b = 0.01$ if an additional prior for λ is used. Accordingly, the hyperparameters for the ridge are $\lambda = 0.168$ or $a = 0.28$, $b = 0.005$

Horseshoe and Horseshoe+ priors

- I can go a few steps further than just aping the frequentist LASSO.
- HS and HS+ priors are another attempt at handling sparsity and variable selection Carvalho et al. (2009), Bhadra et al. (2015).
- They seem to perform better than the LASSO at regularising outliers amongst other things.
- The horseshoe:

$$\begin{aligned} \beta_i &\sim N(0, \lambda_i^2 \tau^2) \\ \lambda_i &\sim C^+(0, 1) \\ \tau &\sim C^+(0, \tau_0^2) \\ \boldsymbol{y} &\sim N(\boldsymbol{\beta}, \sigma_y^2) \end{aligned}$$

- Where τ_0 is a function of our expected number of relevant predictors and some other stuff, Piironen & Vehtari (2017).

The Horseshoe+

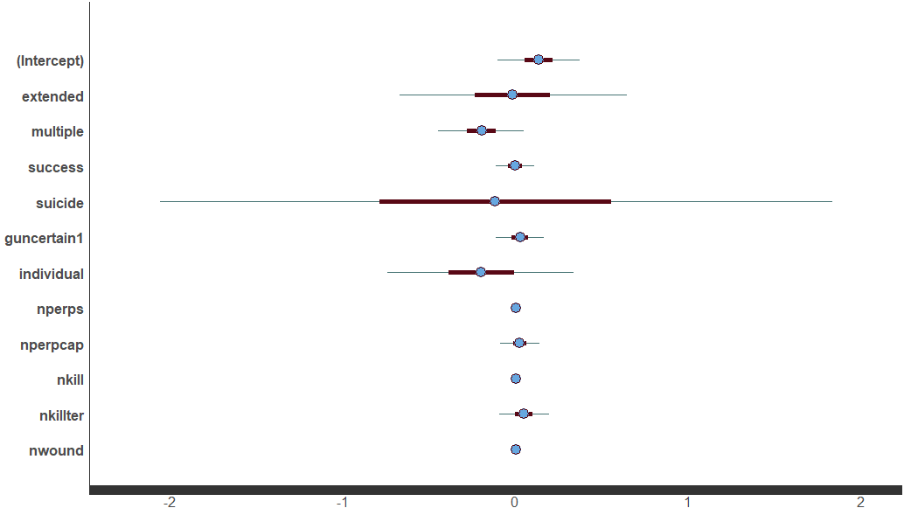
- Pretty similar but I add a half-Cauchy ‘mixing’ variable:

$$\begin{aligned}
\beta_i &\sim N(0, \lambda_i^2 \tau^2) \\
\lambda_i &\sim C^+(0, \eta_i) \\
\eta_i &\sim C^+(0, 1) \\
\tau &\sim C^+(0, \tau_0^2) \\
\boldsymbol{y} &\sim N(\boldsymbol{\beta}, \sigma_y^2)
\end{aligned}$$

- This improves on the HS’s ability to detect signals when signals are ‘ultra-sparse’.
- Basically the HS+ has heavier tails and more mass near the origin so you get the best of both worlds in setting stuff to 0 and detecting outliers (i.e. relevant variables).

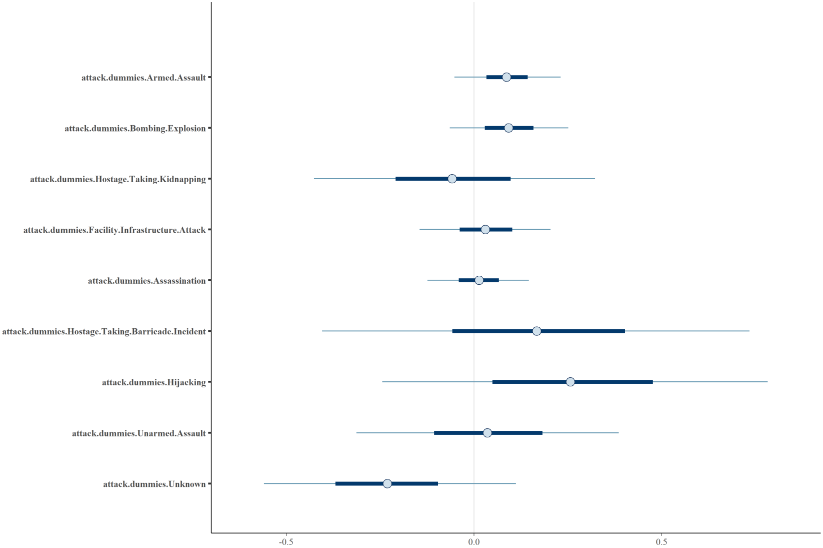
Results II

OLS

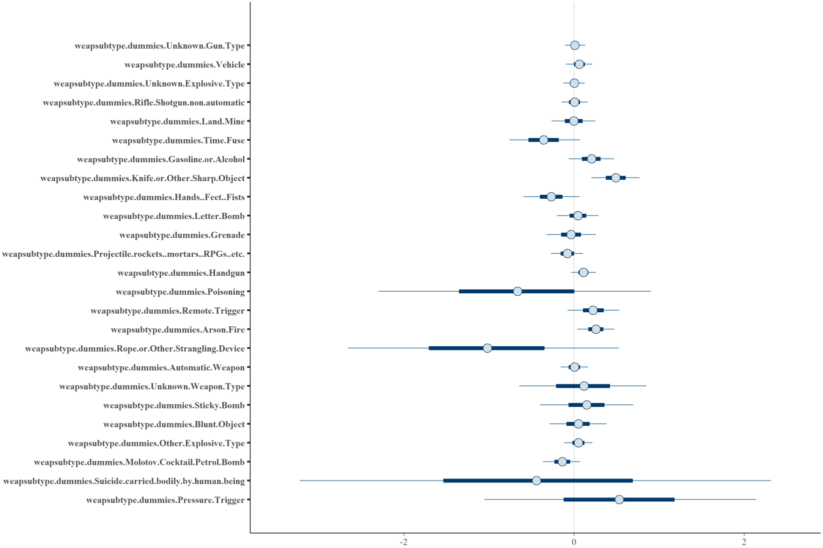


(Intercept)
extended
multiple
success
suicide
guncertain1
individual
nperps
nperpcap
nkill
nkillter
nwound
-2
-1
0
1
2

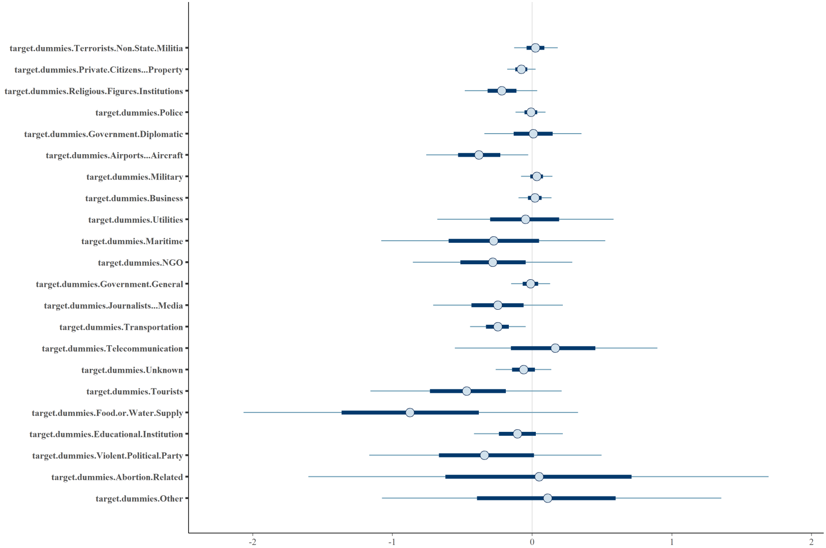
OLS - Attack Type



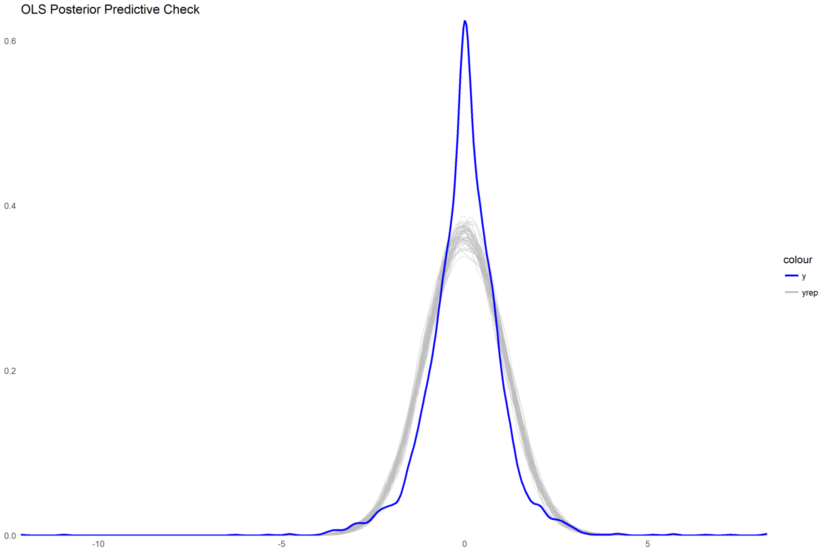
OLS - Weapon Type



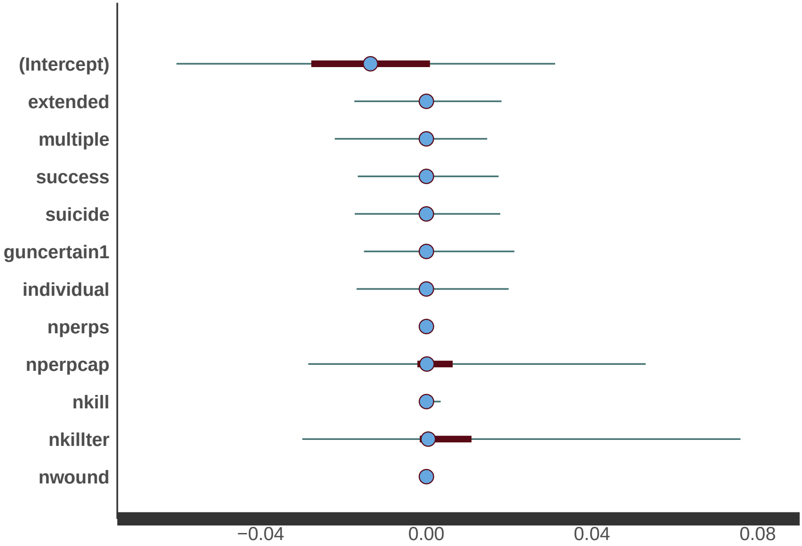
OLS - Target Type



OLS - Posterior Predictive Check

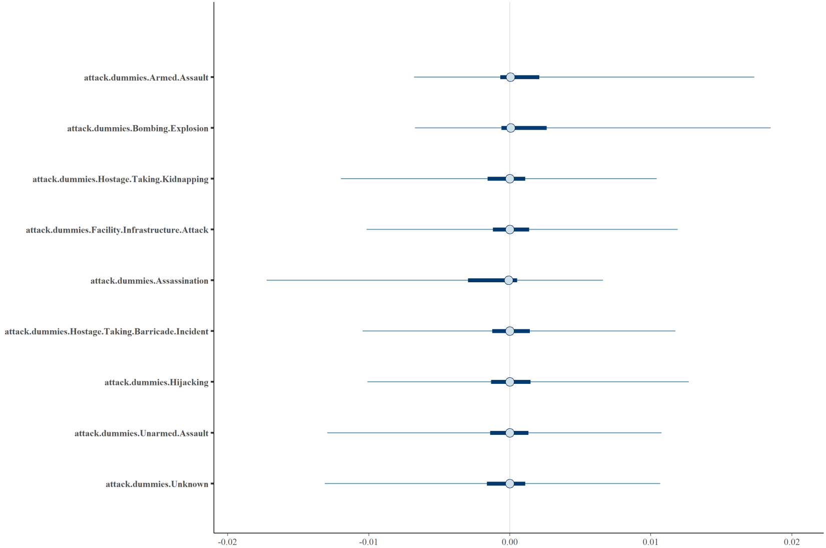


LASSO

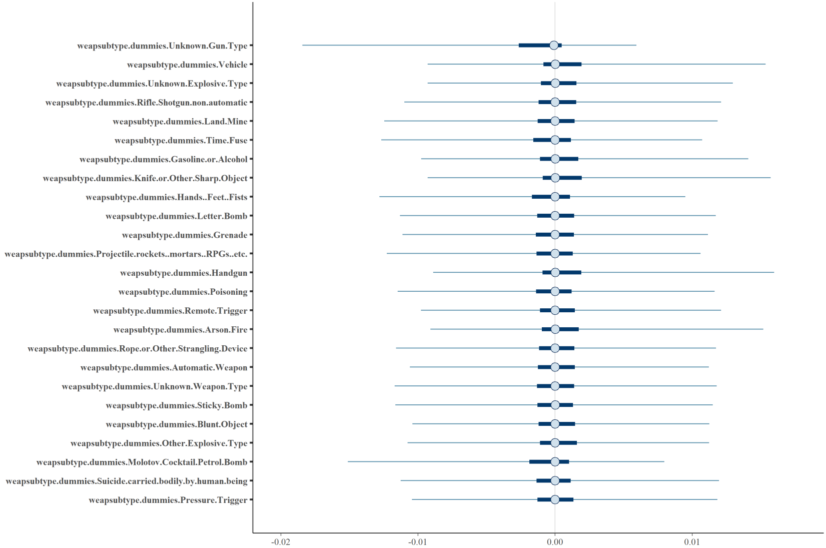


(Intercept)
extended
multiple
success
suicide
guncertain1
individual
nperps
nperpcap
nkill
nkillter
nwound
−0.04
0.00
0.04
0.08

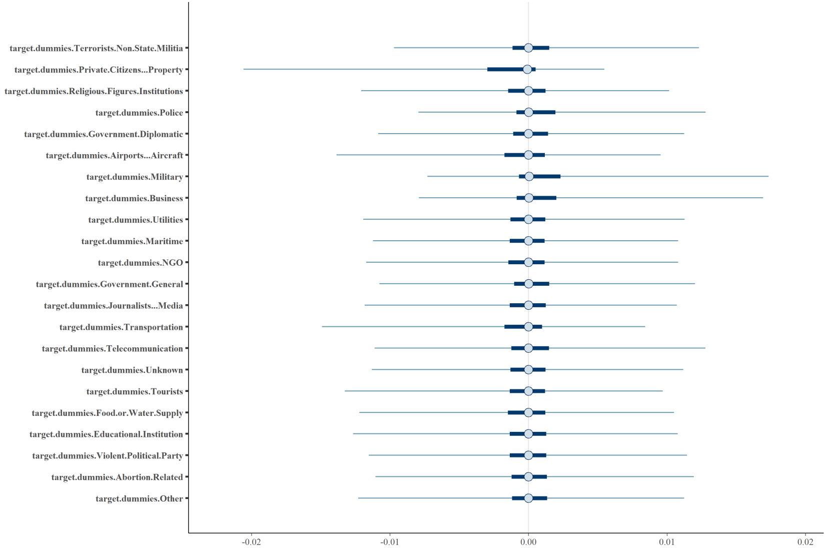
LASSO - Attack Type



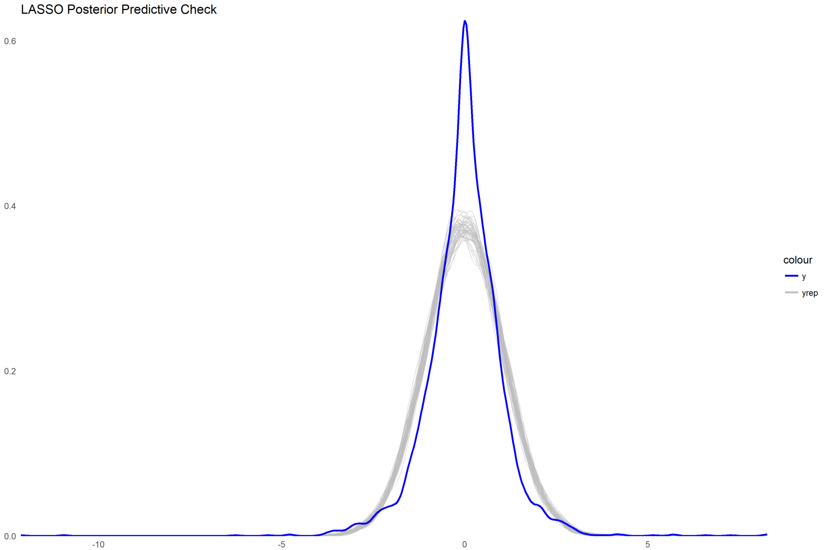
LASSO - Weapon Type



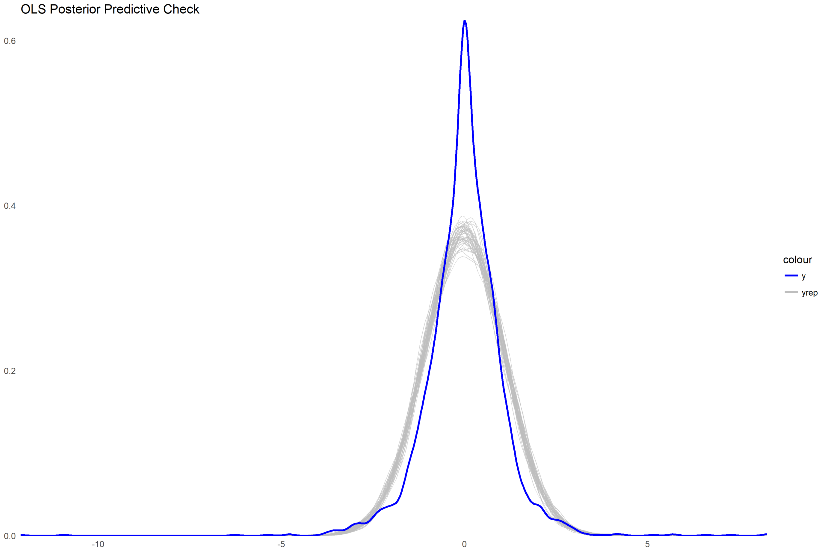
LASSO - Target Type



LASSO - Posterior Predictive Check



OLS - PPC


OLS Posterior Predictive Check
0.6
0.4
0.2
0.0
-10
-5
0
5
colour
y
yrep

Conclusion

- ‘Large’ events pn the whole negatively impact markets but effects disappear quickly as I move from larger to smaller events.
- Pinning down these ‘large’ events statistically instead of heuristically isn’t going too hot right now.