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)
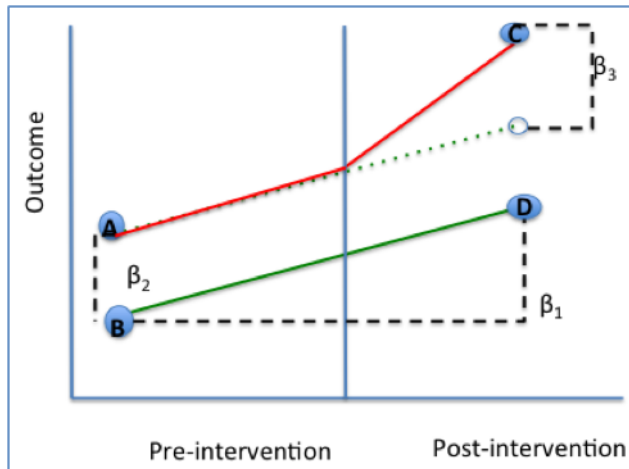
Methodology

Event Study

Event Study I
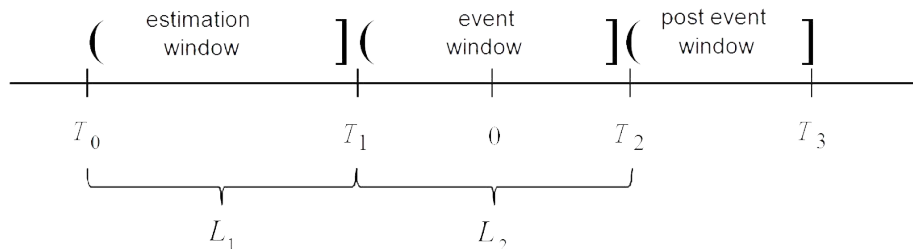
- Formulae for cumulative abnormal returns:

  - $AR_{i,\tau} = R_{i,\tau} - E[R_{i,\tau}|\Omega_{i,\tau}]$
  - $CAR_{i(\tau_1,\tau_2)} = \sum_{t=\tau_1}^{\tau_2} AR_{i,t}$

- 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 ~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
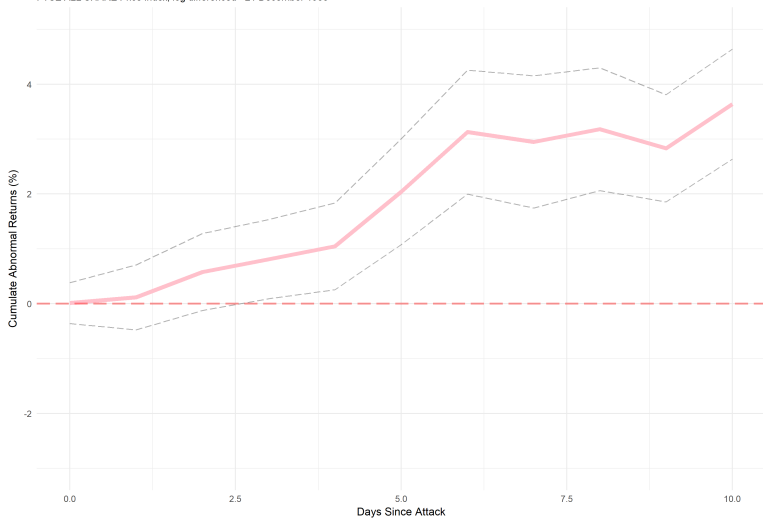
London 7/7 Bombings, Cumulative Abnormal Returns
FTSE ALL SHARE Price Index, log differenced - 7 July 2005
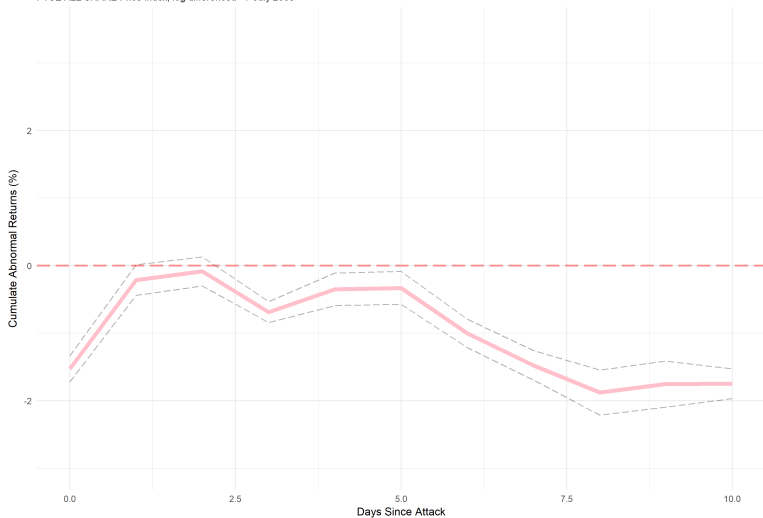
Omagh Bombing, Cumulative Abnormal Returns

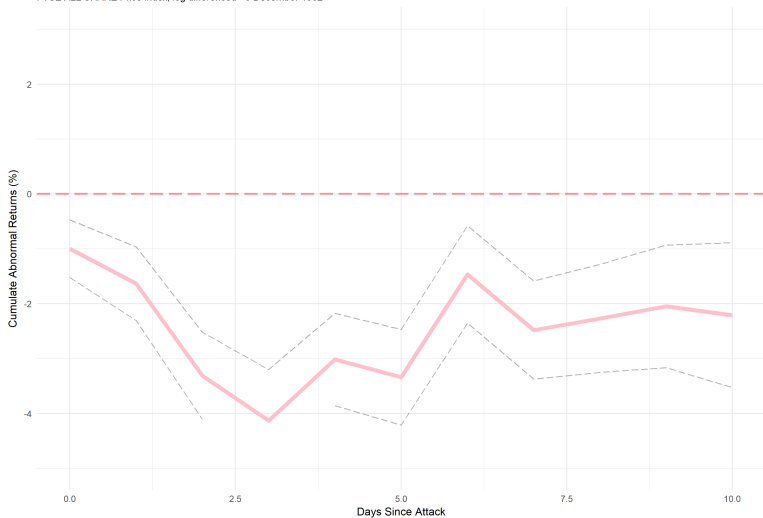FTSE ALL SHARE Price Index, log differenced - 15 August 1998
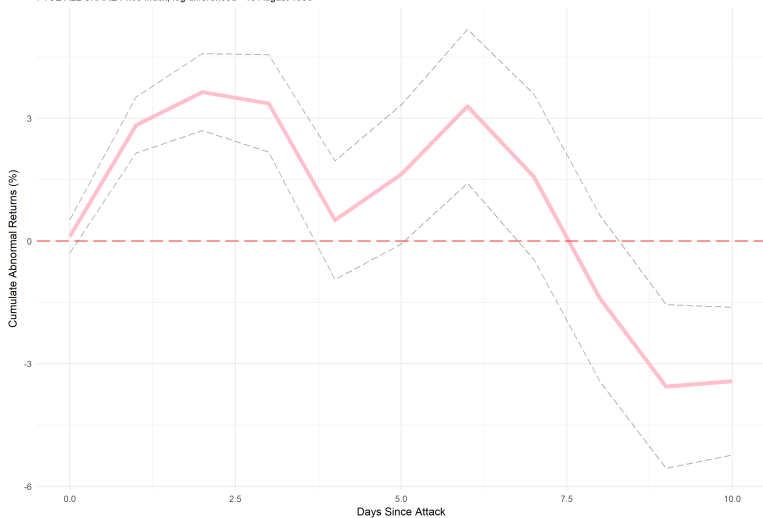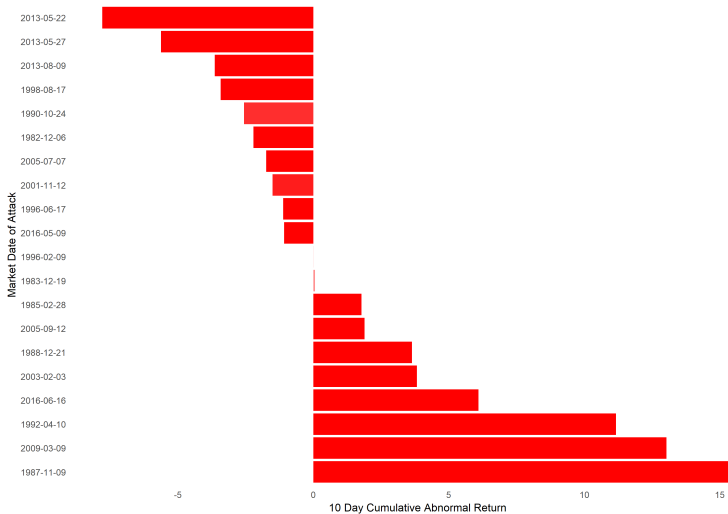
1996 Manchester Bombing, Cumulative Abnormal Returns

FTSE ALL SHARE Price Index, log differenced - 15 June 1996
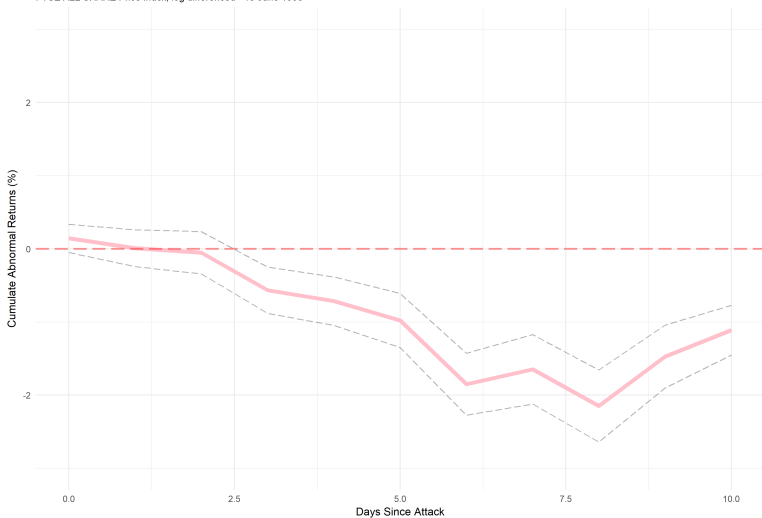
Droppin Well Disco Bombing, Cumulative Abnormal Returns

FTSE ALL SHARE Price Index, log differenced - 6 December 1982
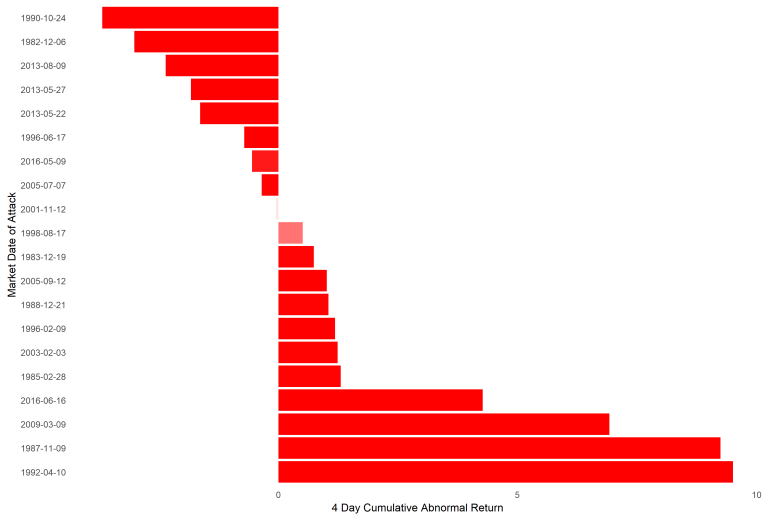
Five Largest Events Per Decade

10 Day Cumulative Abnormal Returns in Response to Terror Event
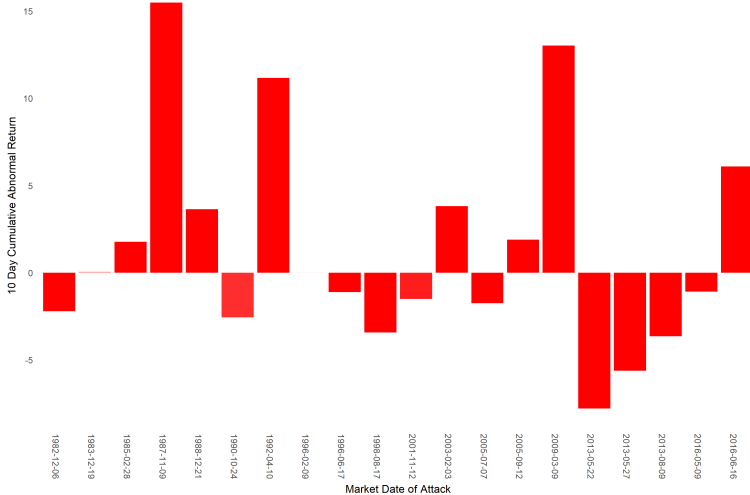Top 5 Events per Decade

4 Day Cumulative Abnormal Returns in Response to Terror Event
Top 5 Events per Decade

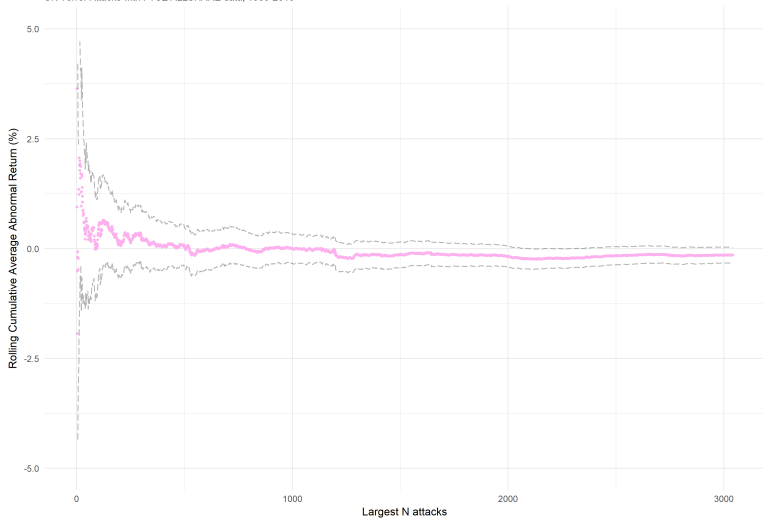10 Day Cumulative Abnormal Returns in Response to Terror Event
Top 5 Events per Decade
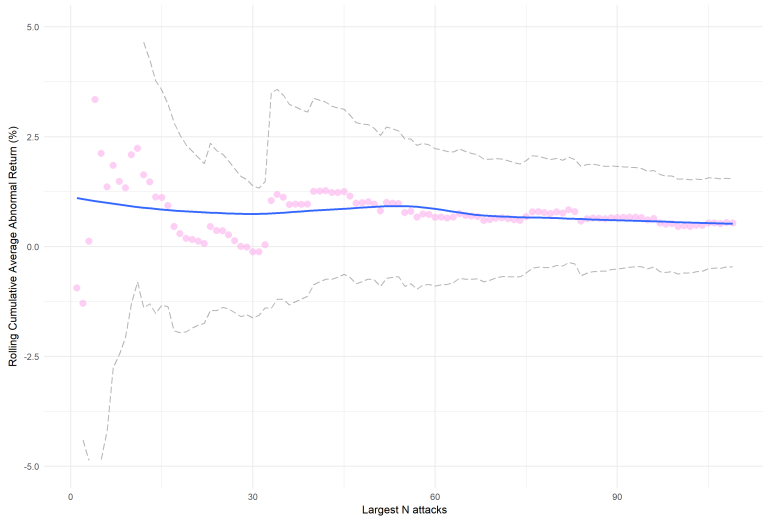
Cumulative Average Abnormal Returns

Rolling mean of Cumulative Abnormal Returns

UK Terror Attacks with FTSE ALLSHARE data, 1980-2016

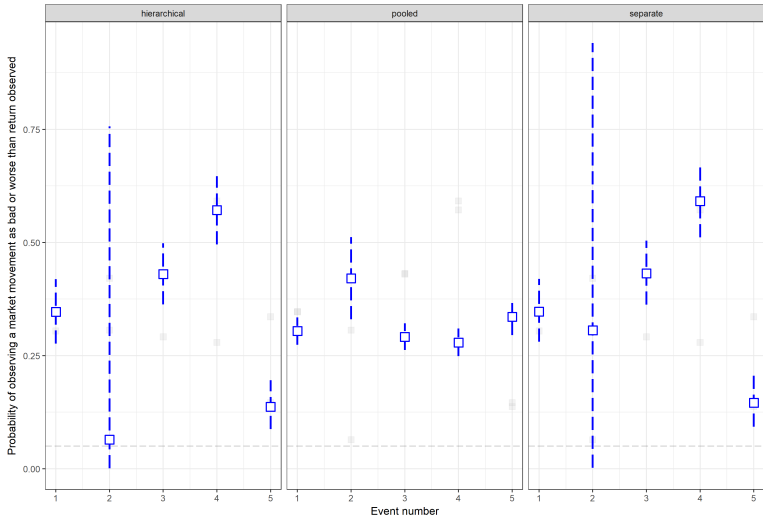Rolling mean of Cumulative Abnormal Returns, screened

UK Terror Attacks with FTSE ALLSHARE data, 1980-2016

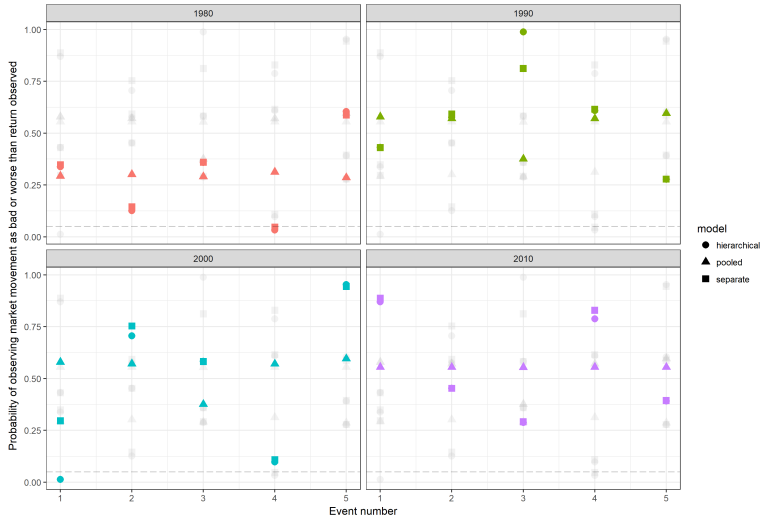# Conditional Probability Results

Conditional Probability of observing more extreme market return on day of attack
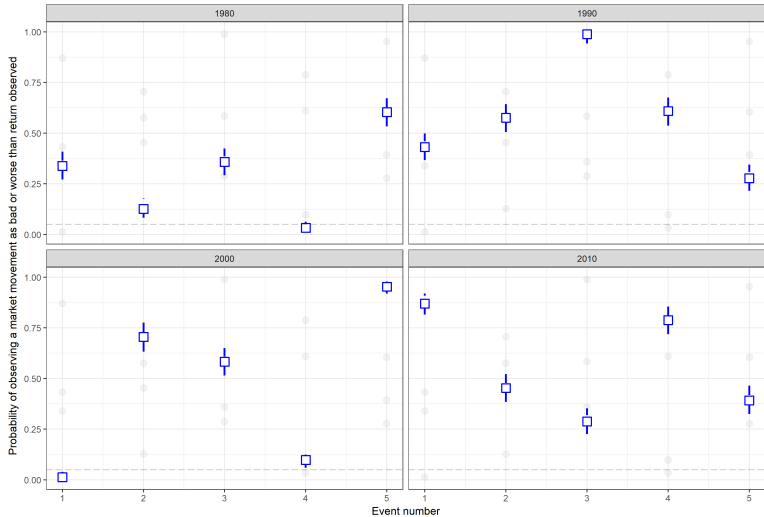5 largest attacks

Conditional Probability of observing more extreme return on day of attack

5 largest attacks per decade

Conditional Probability of observing more extreme market return on day of attack
5 largest attacks per decade - hierarchical model only

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)).
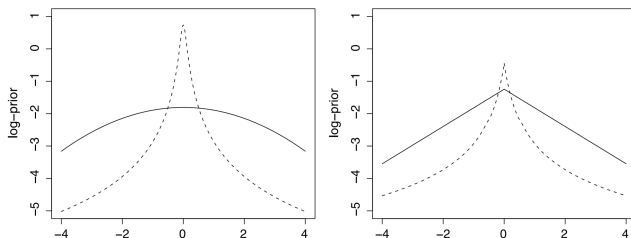 - Use a hierarchical shrinkage model with laplace priors on the regression parameters, Park & Casella (2008).

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 λ = 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 λ = 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:

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

- 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:

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

- 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

Quick Overview of Predictors

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.