

Final Project - Bayesian Analysis

```
library(readxl)
library(dplyr)
library(tidyr)
library(lubridate)
library(stringr)
library(lme4)
```

```
load("beatspy.RData")
```

Frequentist

```
## boundary (singular) fit: see help('isSingular')
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##   Family: binomial   ( logit )
## Formula: beat_spy ~ log_pe + div_yield + (1 + log_pe + div_yield | Ticker)
##   Data: m3_df
## Control: glmerControl(optimizer = "bobyqa")
##
##           AIC          BIC      logLik -2*log(L)  df.resid
##       4632.9      4688.0   -2307.4    4614.9      3391
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
```

	Health Care	Information Technology	Consumer Staples	Industrials	Utilities	Financials	Materials
(Intercept)	−0.846 (1.388)	1.524 (0.741)	0.684 (1.268)	−0.559 (0.571)	0.512 (0.566)	−2.651 (1.001)	0.231 (0.726)
log_pe	0.215 (0.403)	−0.304 (0.212)	−0.262 (0.373)	0.049 (0.153)	0.022 (0.168)	0.791 (0.293)	0.000 (0.214)
div_yield	−0.044 (0.097)	−0.279 (0.089)	−0.181 (0.090)	−0.012 (0.052)	−0.184 (0.060)	−0.038 (0.096)	−0.074 (0.081)
Num.Obs.	94	283	306	189	603	321	577
AIC	131.3	387.2	395.5	257.9	826.0	427.6	803.8
BIC	138.9	398.2	406.7	267.7	839.2	438.9	816.9
Log.Lik.	−62.641	−190.622	−194.752	−125.971	−410.016	−210.811	−398.895
RMSE	0.49	0.49	0.47	0.49	0.49	0.48	0.50

```

## -1.1874 -0.9363 -0.6846 1.0067 2.9505
##
## Random effects:
## Groups Name Variance Std.Dev. Corr
## Ticker (Intercept) 0.289481 0.53803
## log_pe 0.012842 0.11332 -1.00
## div_yield 0.007972 0.08928 -1.00 1.00
## Number of obs: 3400, groups: Ticker, 406
##
## Fixed effects:
## Estimate Std. Error z value Pr(>|z|)
## (Intercept) 0.24602 0.20147 1.221 0.222
## log_pe 0.02221 0.05797 0.383 0.702
## div_yield -0.17073 0.02119 -8.057 7.84e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) log_pe
## log_pe -0.949
## div_yield -0.565 0.335
## optimizer (bobyqa) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')

##
## Call:
## glm(formula = beat_spy ~ log_pe + div_yield + factor(gics_sector_name),
## family = binomial(link = "logit"), data = m3_df)
##
## Coefficients:
## Estimate Std. Error z value
## (Intercept) -0.51439 0.31086 -1.655
## log_pe 0.16173 0.06488 2.493
## div_yield -0.10129 0.02318 -4.370
## factor(gics_sector_name)Consumer Discretionary 0.25790 0.24538 1.051
## factor(gics_sector_name)Consumer Staples -0.26459 0.24560 -1.077
## factor(gics_sector_name)Energy -0.02855 0.26369 -0.108
## factor(gics_sector_name)Financials 0.42514 0.22947 1.853
## factor(gics_sector_name)Health Care -0.12594 0.24359 -0.517
## factor(gics_sector_name)Industrials 0.31252 0.23072 1.355
## factor(gics_sector_name)Information Technology 0.67038 0.24352 2.753
## factor(gics_sector_name)Materials -0.01109 0.25882 -0.043
## factor(gics_sector_name)Real Estate -0.39848 0.26779 -1.488
## factor(gics_sector_name)Utilities 0.12672 0.24909 0.509
## Pr(>|z|)
## (Intercept) 0.09798 .
## log_pe 0.01267 *
## div_yield 1.24e-05 ***
## factor(gics_sector_name)Consumer Discretionary 0.29324
## factor(gics_sector_name)Consumer Staples 0.28134
## factor(gics_sector_name)Energy 0.91379
## factor(gics_sector_name)Financials 0.06392 .
## factor(gics_sector_name)Health Care 0.60513
## factor(gics_sector_name)Industrials 0.17555

```

```

## factor(gics_sector_name)Information Technology 0.00591 **
## factor(gics_sector_name)Materials 0.96582
## factor(gics_sector_name)Real Estate 0.13675
## factor(gics_sector_name)Utilities 0.61092
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 4692.6 on 3399 degrees of freedom
## Residual deviance: 4553.0 on 3387 degrees of freedom
## AIC: 4579
##
## Number of Fisher Scoring iterations: 4

##
## Call:
## glm(formula = beat_spy ~ log_pe + div_yield * factor(gics_sector_name),
##      family = binomial(link = "logit"), data = m3_df)
##
## Coefficients:
##
## Estimate Std. Error
## (Intercept) -0.598294 0.382658
## log_pe 0.141407 0.065402
## div_yield -0.056334 0.072561
## factor(gics_sector_name)Consumer Discretionary 0.651732 0.386631
## factor(gics_sector_name)Consumer Staples -0.061950 0.397369
## factor(gics_sector_name)Energy -0.269860 0.406570
## factor(gics_sector_name)Financials 0.724126 0.350106
## factor(gics_sector_name)Health Care 0.132709 0.362233
## factor(gics_sector_name)Industrials 0.364062 0.355297
## factor(gics_sector_name)Information Technology 1.078496 0.379784
## factor(gics_sector_name)Materials 0.046934 0.386036
## factor(gics_sector_name)Real Estate -0.436358 0.490961
## factor(gics_sector_name)Utilities 0.190843 0.517561
## div_yield:factor(gics_sector_name)Consumer Discretionary -0.149613 0.107978
## div_yield:factor(gics_sector_name)Consumer Staples -0.064631 0.100157
## div_yield:factor(gics_sector_name)Energy 0.050386 0.088010
## div_yield:factor(gics_sector_name)Financials -0.105227 0.087464
## div_yield:factor(gics_sector_name)Health Care -0.107264 0.105975
## div_yield:factor(gics_sector_name)Industrials 0.002932 0.103243
## div_yield:factor(gics_sector_name)Information Technology -0.161282 0.107027
## div_yield:factor(gics_sector_name)Materials -0.012621 0.096039
## div_yield:factor(gics_sector_name)Real Estate -0.000487 0.103716
## div_yield:factor(gics_sector_name)Utilities -0.026034 0.120654
## z value Pr(>|z|)
## (Intercept) -1.564 0.11793
## log_pe 2.162 0.03061 *
## div_yield -0.776 0.43754
## factor(gics_sector_name)Consumer Discretionary 1.686 0.09186 .
## factor(gics_sector_name)Consumer Staples -0.156 0.87611
## factor(gics_sector_name)Energy -0.664 0.50685
## factor(gics_sector_name)Financials 2.068 0.03861 *
## factor(gics_sector_name)Health Care 0.366 0.71409

```

```

## factor(gics_sector_name)Industrials          1.025  0.30552
## factor(gics_sector_name)Information Technology 2.840  0.00451 **
## factor(gics_sector_name)Materials            0.122  0.90323
## factor(gics_sector_name)Real Estate          -0.889  0.37412
## factor(gics_sector_name)Utilities            0.369  0.71232
## div_yield:factor(gics_sector_name)Consumer Discretionary -1.386  0.16587
## div_yield:factor(gics_sector_name)Consumer Staples -0.645  0.51874
## div_yield:factor(gics_sector_name)Energy      0.573  0.56698
## div_yield:factor(gics_sector_name)Financials -1.203  0.22894
## div_yield:factor(gics_sector_name)Health Care -1.012  0.31146
## div_yield:factor(gics_sector_name)Industrials  0.028  0.97734
## div_yield:factor(gics_sector_name)Information Technology -1.507  0.13183
## div_yield:factor(gics_sector_name)Materials -0.131  0.89544
## div_yield:factor(gics_sector_name)Real Estate -0.005  0.99625
## div_yield:factor(gics_sector_name)Utilities -0.216  0.82916
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 4692.6 on 3399 degrees of freedom
## Residual deviance: 4542.1 on 3377 degrees of freedom
## AIC: 4588.1
##
## Number of Fisher Scoring iterations: 4

```

Model Comparison

```

##           Model df      AIC
## 1 pooled_fe 13 4579.022
## 2 pooled_fe_interact 23 4588.136
## 3 sector_models 33 4590.064
## 4 mixed_random_slopes 9 4632.865

##           Model df      BIC
## 1 pooled_fe 13 4658.732
## 2 mixed_random_slopes 9 4688.048
## 3 pooled_fe_interact 23 4729.162
## 4 sector_models 33 4792.405

```

(to-do – LOOCV)

Bayesian

Model 1 (Logistic)

$$Y_{i,t} \sim \text{Bernoulli}(p_{i,t})$$

$$\text{logit}(p_{i,t}) = \beta_0 + \beta_1 + \log(PE_{i,t}) + \beta_2 \text{DivYield}_{i,t}$$

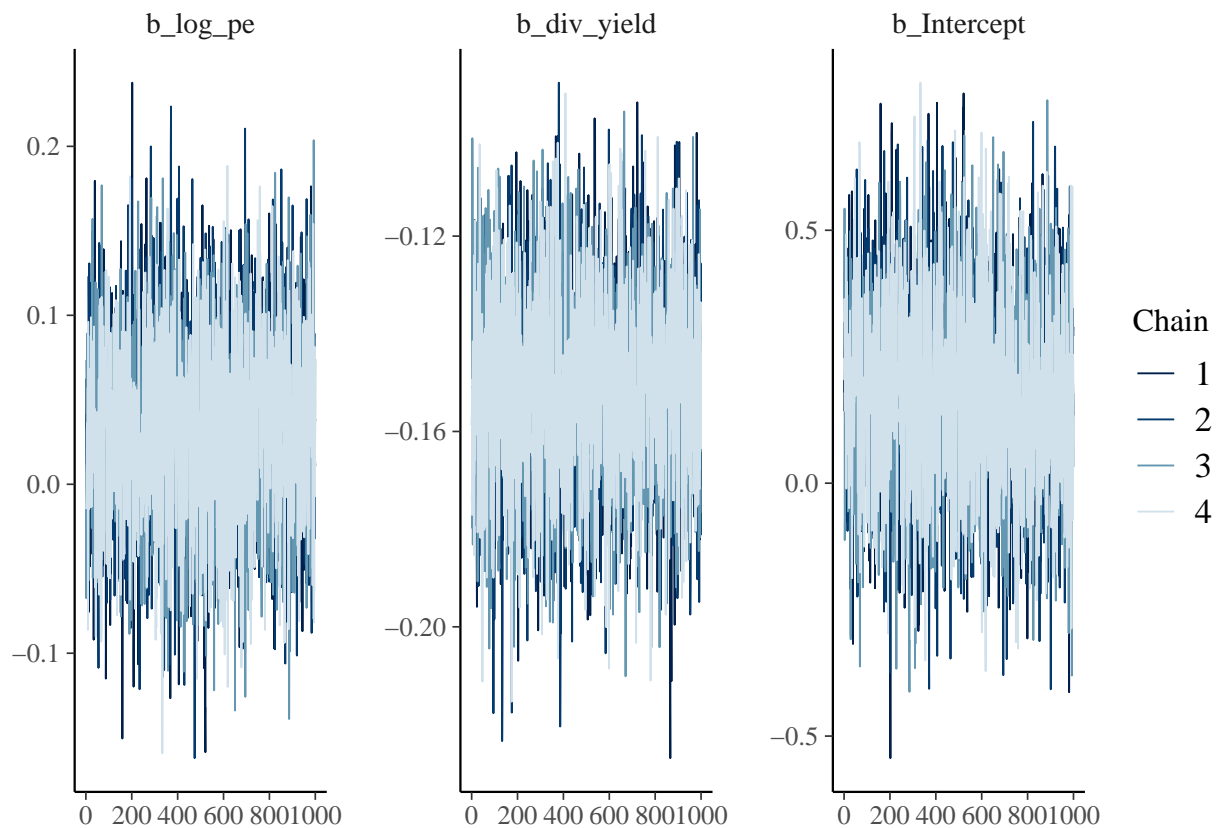
```
## Compiling Stan program...
```

```
## Trying to compile a simple C file
```

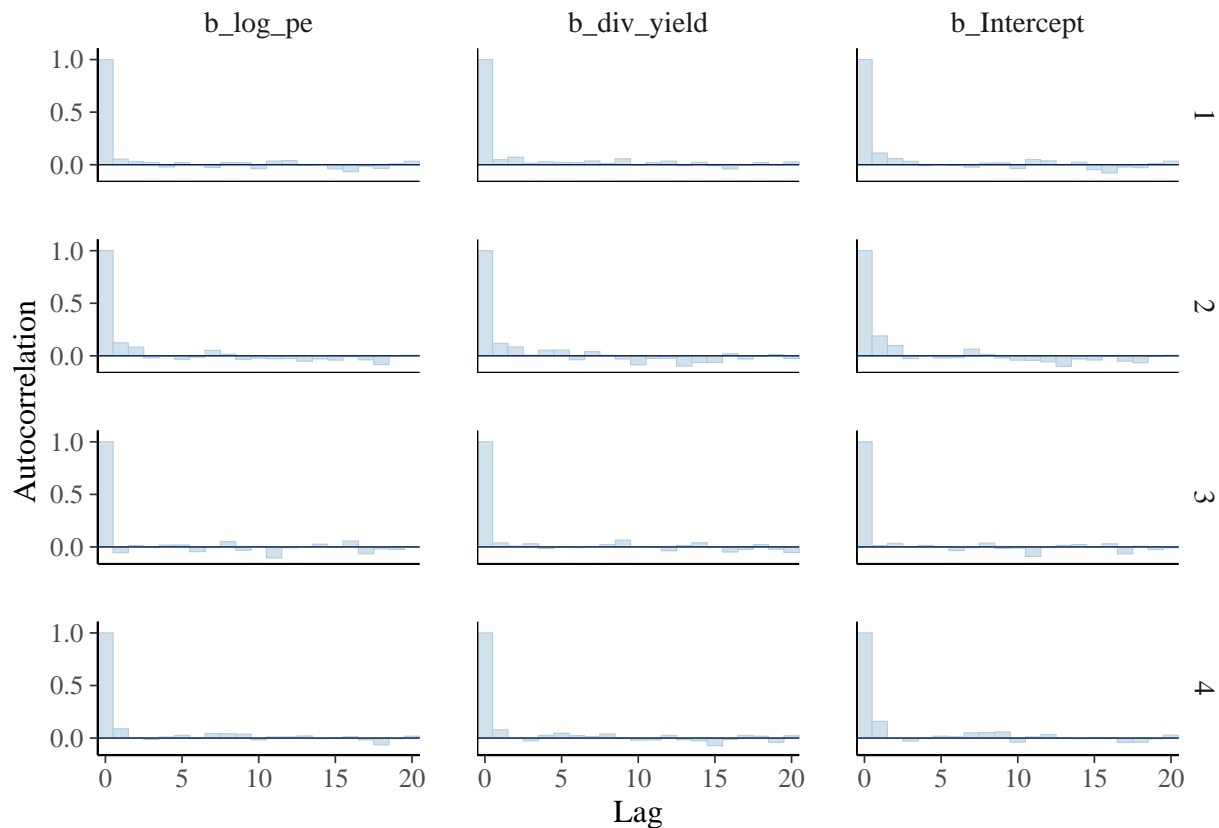
```
## Start sampling
```

```
##           Estimate Est.Error 1-95% CI u-95% CI   Rhat Bulk_ESS
## Intercept  0.17273278 0.18791917 -0.1830719  0.5376506 1.001122 3007.931
## log_pe     0.03149262 0.05432937 -0.0760189  0.1343352 1.001685 3368.702
## div_yield -0.15189077 0.01951898 -0.1906835 -0.1138507 1.000259 2819.099
##           Tail_ESS
## Intercept 2906.451
## log_pe    3373.531
## div_yield 2796.484
```

Rhats are ~ 1 and effective sample sizes $\gg 100$



No discernable pattern from trace plots



acfs fall off quickly

Model 2 (Nested random intercepts)

$$\text{logit}(p_{i,t}) = \beta_0 + \beta_1 \log(PE_{i,t}) + \beta_2 \text{DivYield}_{i,t} + u_j + v_i$$

```
## Compiling Stan program...
```

```
## Trying to compile a simple C file
```

```
## Start sampling
```

```
## Family: bernoulli
```

```
## Links: mu = logit
```

```
## Formula: beat_spy ~ log_pe + div_yield + (1 | gics_sector_name/Ticker)
```

```
## Data: m3_df (Number of observations: 3400)
```

```
## Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
```

```
## total post-warmup draws = 4000
```

```
##
```

```
## Multilevel Hyperparameters:
```

```
## ~gics_sector_name (Number of levels: 11)
```

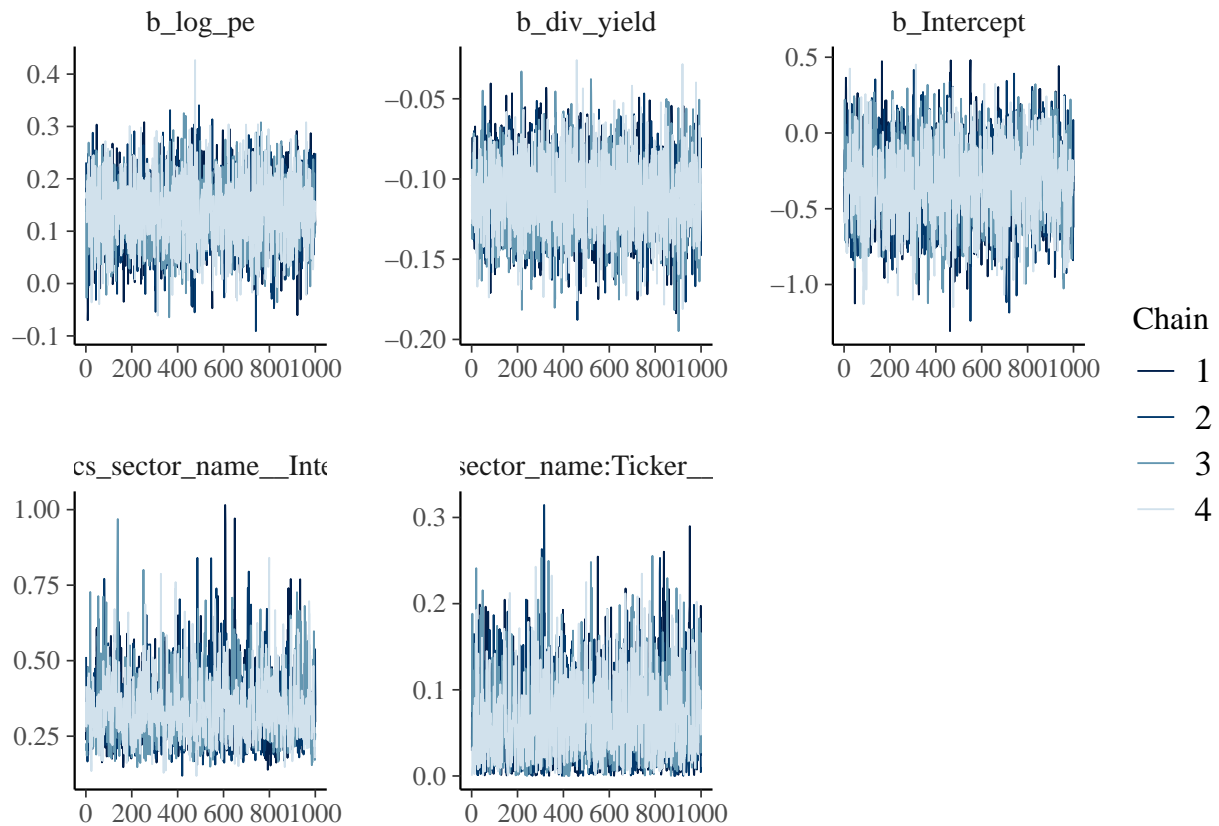
```
## Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
```

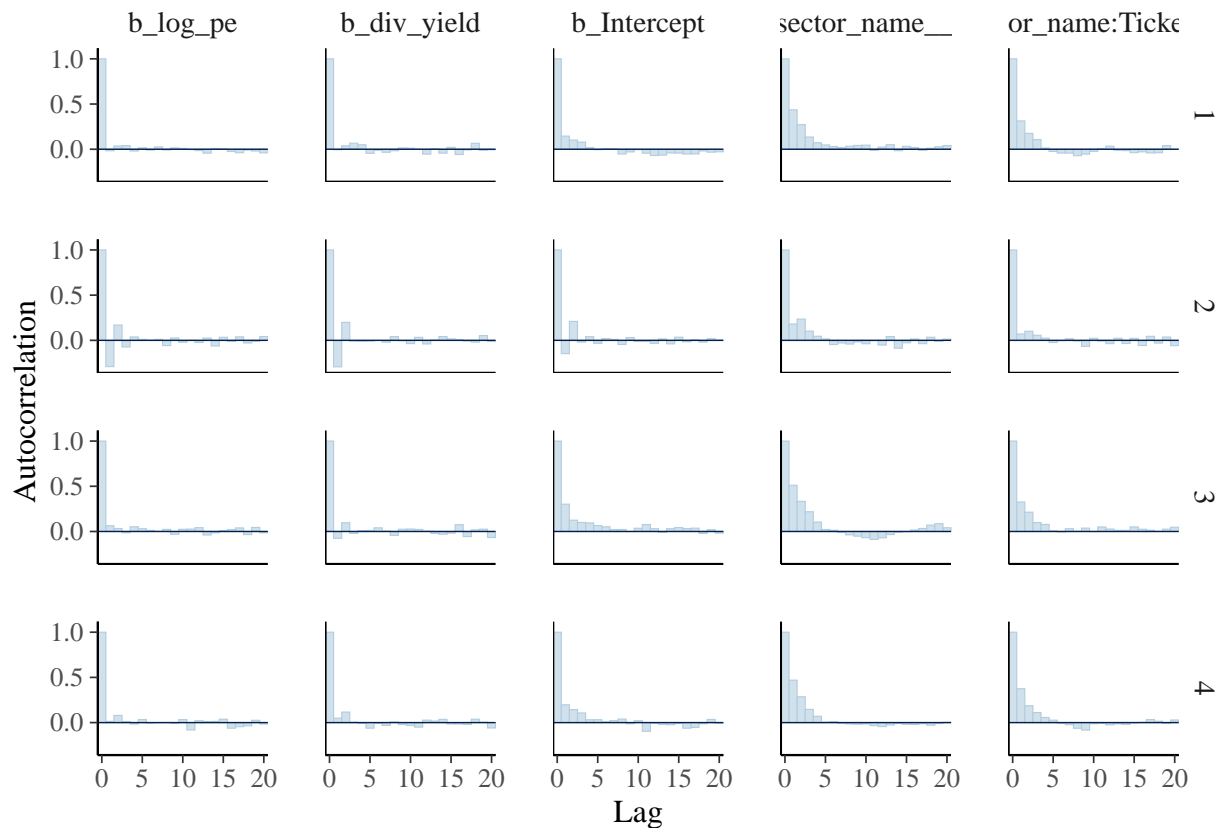
```
## sd(Intercept) 0.34 0.10 0.19 0.59 1.00 1348 2025
```

```
##
```

```
## ~gics_sector_name:Ticker (Number of levels: 406)
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)    0.06     0.05     0.00     0.17 1.00     1607     1590
##
## Regression Coefficients:
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept    -0.32     0.26    -0.82     0.17 1.00     2110     2593
## log_pe        0.14     0.06     0.02     0.26 1.00     3616     2987
## div_yield    -0.11     0.02    -0.15    -0.07 1.00     3638     2948
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

Rhats are all ~1, effective sample sizes » 100





acfs fall off quickly

Model 3 (Mixed Effects + firm-level random slopes/intercepts)

Covariates are centered

```
## Compiling Stan program...

## Trying to compile a simple C file

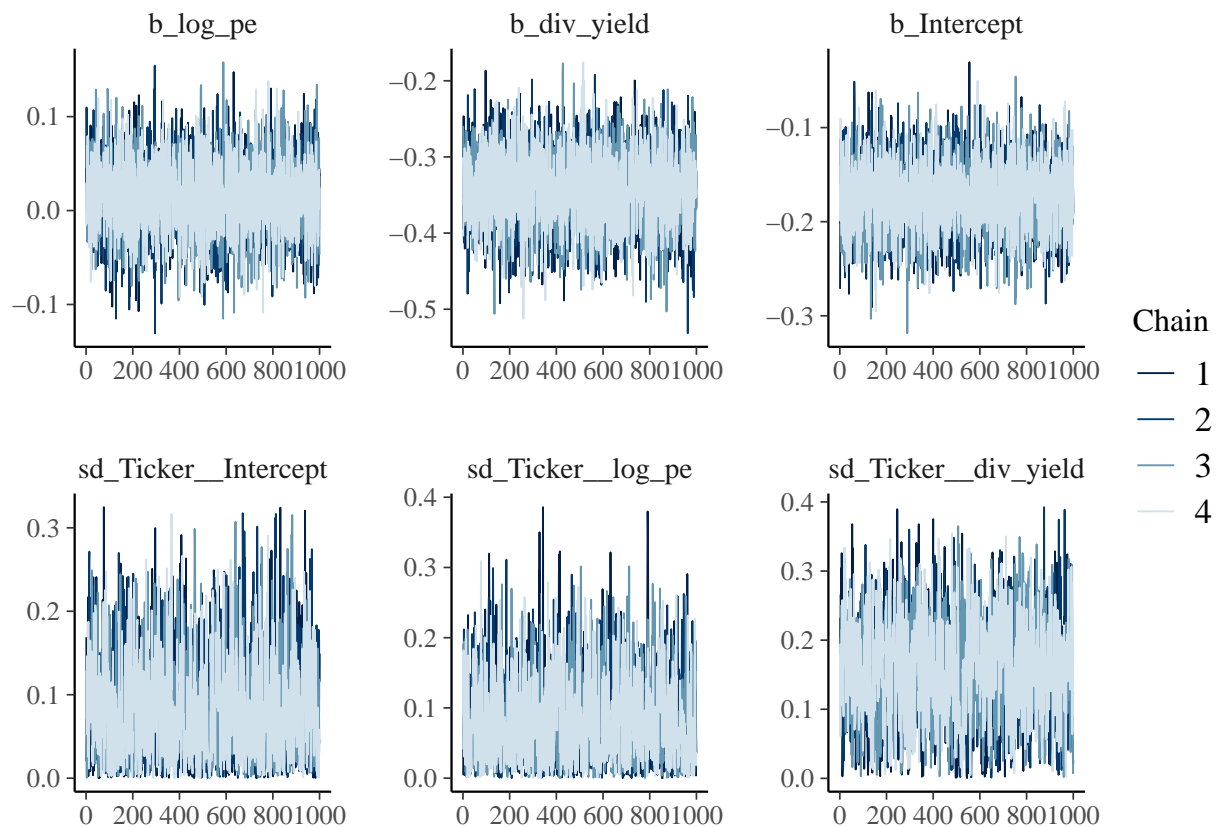
## Start sampling

## Family: bernoulli
## Links: mu = logit
## Formula: beat_spy ~ log_pe + div_yield + (1 + log_pe + div_yield | Ticker)
## Data: mutate(m3_df, log_pe = scale(log_pe), div_yield = (Number of observations: 3400)
## Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##           total post-warmup draws = 4000
##
## Multilevel Hyperparameters:
## ~Ticker (Number of levels: 406)
##
```

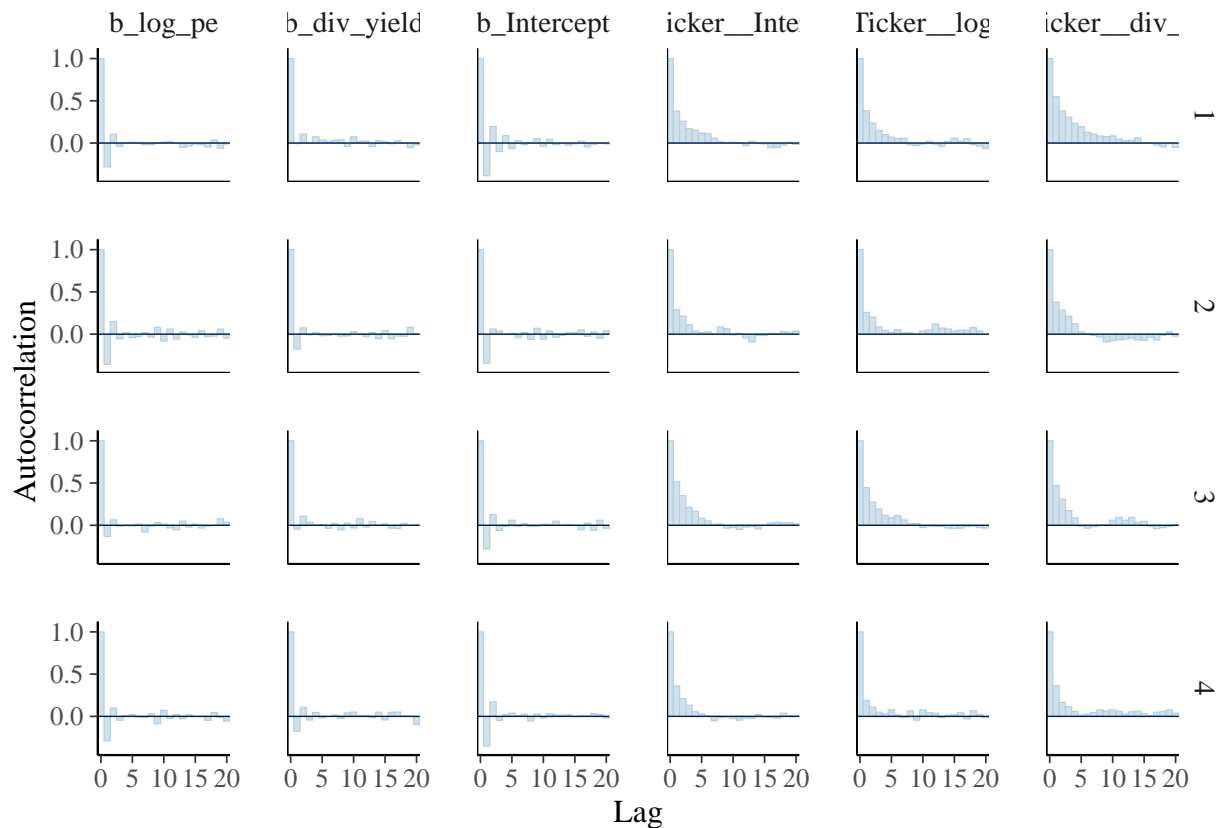
	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS
## sd(Intercept)	0.09	0.06	0.00	0.23	1.00	1265
## sd(log_pe)	0.08	0.06	0.00	0.23	1.00	1412
## sd(div_yield)	0.16	0.07	0.02	0.30	1.00	1070


```
## cor(Intercept,log_pe)      0.03      0.50     -0.87      0.89 1.00      2685
## cor(Intercept,div_yield)   0.10      0.48     -0.83      0.90 1.00      1388
## cor(log_pe,div_yield)      0.20      0.48     -0.78      0.92 1.00      1513
##                               Tail_ESS
## sd(Intercept)              1754
## sd(log_pe)                  2025
## sd(div_yield)               1397
## cor(Intercept,log_pe)      2449
## cor(Intercept,div_yield)    2368
## cor(log_pe,div_yield)      2618
##
## Regression Coefficients:
##      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept    -0.17     0.04   -0.24   -0.10 1.00     6658     3278
## log_pe        0.01     0.04   -0.06    0.09 1.00     6592     3033
## div_yield    -0.34     0.05   -0.44   -0.25 1.00     3832     3085
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

Rhats are ~1 and effective sample sizes » 100



No discernable pattern from trace plots



Model 4 (Pooled + sector FE)

```
## Compiling Stan program...
```

```
## Trying to compile a simple C file
```

```
## Start sampling
```

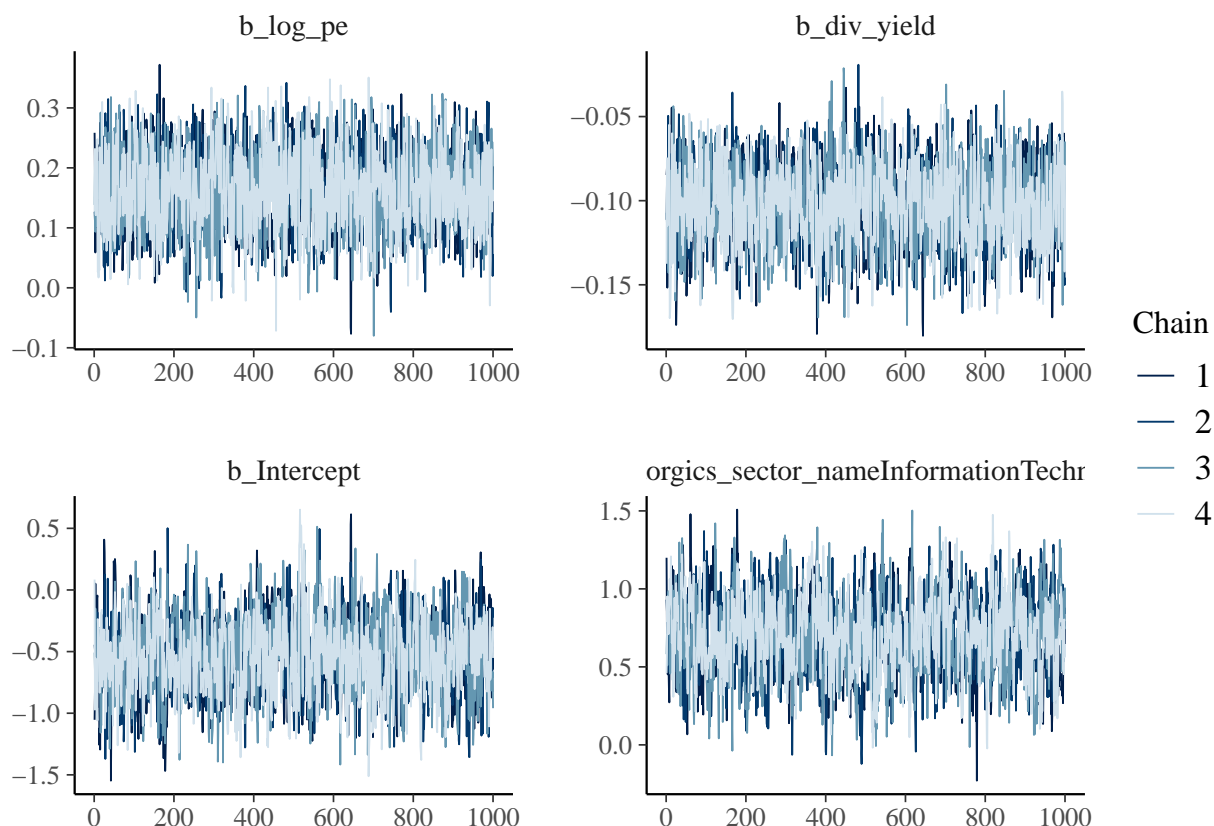
```
## Family: bernoulli
## Links: mu = logit
## Formula: beat_spy ~ log_pe + div_yield + factor(gics_sector_name)
## Data: m3_df (Number of observations: 3400)
## Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
## total post-warmup draws = 4000
##
```

```
## Regression Coefficients:
```

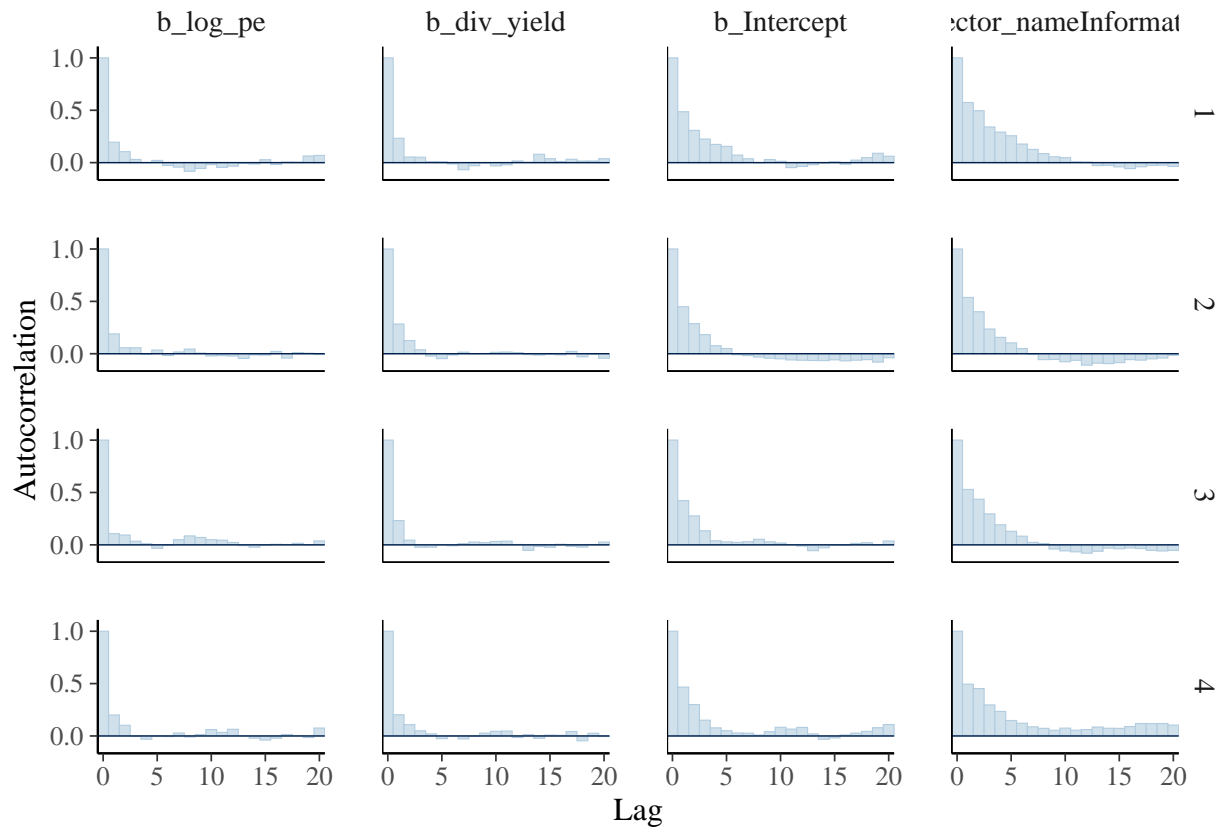
	Estimate	Est.Error	1-95% CI
## Intercept	-0.53	0.31	-1.15
## log_pe	0.16	0.07	0.04
## div_yield	-0.10	0.02	-0.15
## factorgics_sector_nameConsumerDiscretionary	0.28	0.25	-0.23
## factorgics_sector_nameConsumerStaples	-0.25	0.25	-0.75
## factorgics_sector_nameEnergy	-0.01	0.27	-0.53
## factorgics_sector_nameFinancials	0.45	0.23	-0.00

```
## factorgics_sector_nameHealthCare          -0.11      0.25    -0.61
## factorgics_sector_nameIndustrials         0.33      0.23    -0.13
## factorgics_sector_nameInformationTechnology 0.69      0.25     0.21
## factorgics_sector_nameMaterials           0.01      0.26    -0.52
## factorgics_sector_nameRealEstate          -0.38      0.27    -0.91
## factorgics_sector_nameUtilities           0.15      0.25    -0.35
##
## u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept          0.08 1.00    1206    1782
## log_pe             0.29 1.00    2550    2373
## div_yield          -0.06 1.00    2367    2615
## factorgics_sector_nameConsumerDiscretionary 0.78 1.00     889    1279
## factorgics_sector_nameConsumerStaples       0.24 1.00     837    1187
## factorgics_sector_nameEnergy                0.52 1.00     945    1424
## factorgics_sector_nameFinancials            0.92 1.00     784    1064
## factorgics_sector_nameHealthCare            0.39 1.00     877    1298
## factorgics_sector_nameIndustrials           0.79 1.00     764    1071
## factorgics_sector_nameInformationTechnology 1.18 1.00     855    1431
## factorgics_sector_nameMaterials             0.52 1.00     915    1599
## factorgics_sector_nameRealEstate            0.16 1.00     913    1482
## factorgics_sector_nameUtilities             0.65 1.00     871    1256
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

Rhats are ~1 and effective sample sizes » 100



No discernable pattern from trace plots



Model Comparison

##		elpd_diff	se_diff
##	bayes_fe	0.0	0.0
##	bayes_model2	-0.3	1.2
##	bayes_model11	-22.5	8.1
##	bayes_model13	-24.9	7.9

LOOCV favors the pooled model with sector fixed effects and the model with nested random intercepts over the baseline pooled model and mixed effects model w/ firm-level random intercepts and slopes.

The sector FE and nested random intercepts models are generally comparable (firm-level variation may be small)