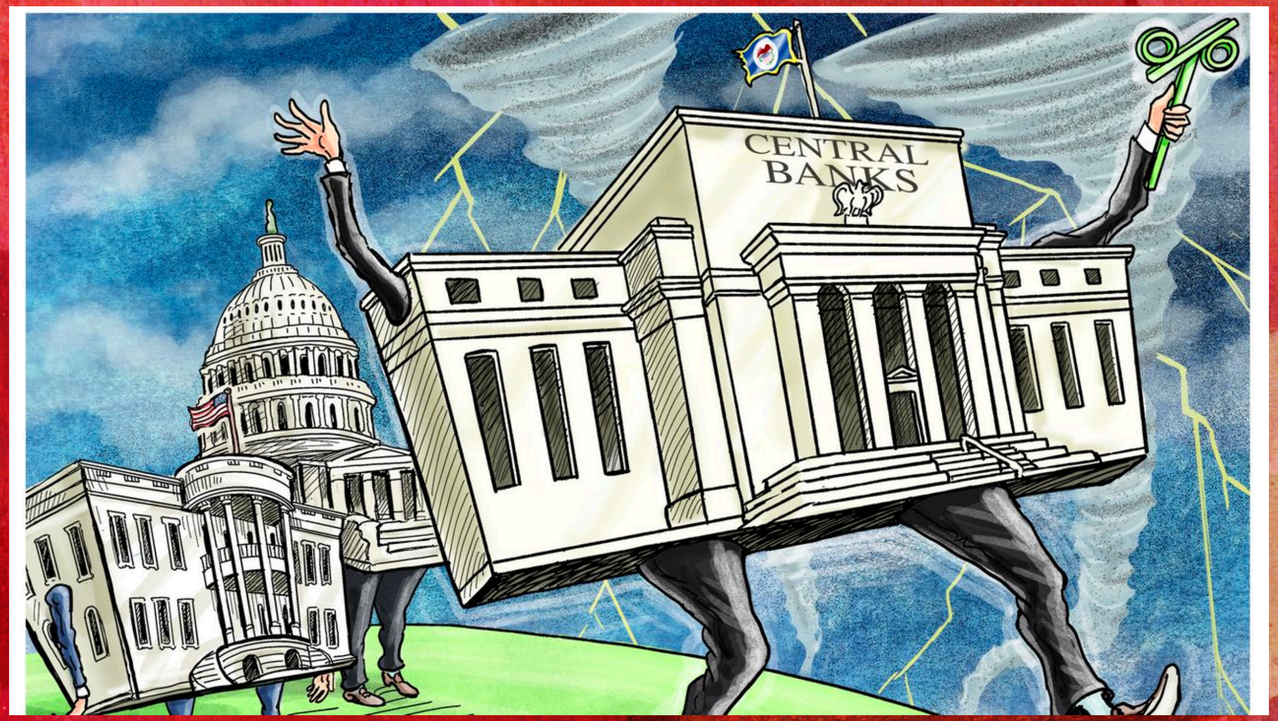

REPLICATION OF 'A TEXTUAL TAYLOR RULE: ESTIMATING CENTRAL BANK PREFERENCES COMBINING TOPIC AND SCALING METHODS'

Han Li, CFA
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ARTICLE

A textual Taylor rule: estimating central bank preferences combining topic and scaling methods*

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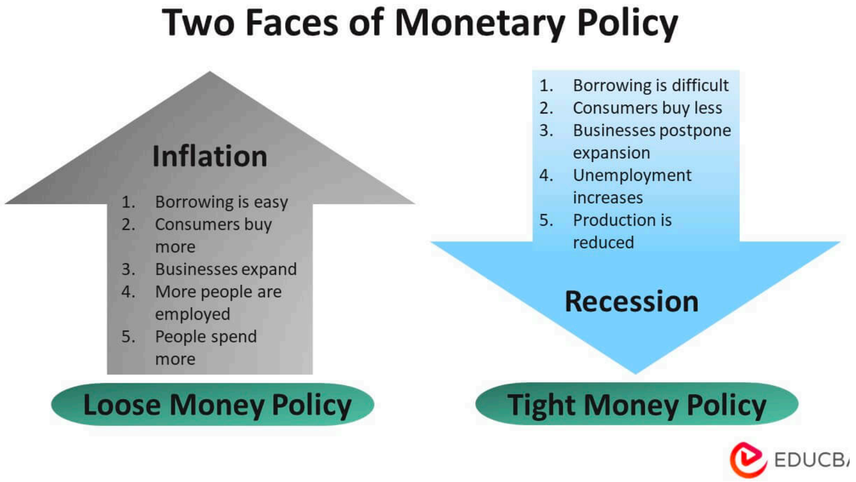
Abstract
Scholars often use voting data to estimate central bankers' policy preferences but consensus voting is commonplace. To get around this, we combine topic-based text analysis and scaling methods to generate theoretically motivated comparative measures of central bank preferences on the US Federal Open Market Committee (FOMC) leading up to the financial crisis in a way that does not depend on voting behavior. We apply these measures to a number of applications in the literature. For example, we find that FOMC members that are Federal Reserve Bank Presidents from districts experiencing higher unemployment are also more likely to emphasize unemployment in their speech. We also confirm that committee members on schedule to vote are more likely to express consensus opinion than their off schedule voting counterparts.

INTRODUCTION

- Research objective: measure central bank policy preference using topic based text analysis through Taylor's rule
- Main contribution: provide a strategy that estimate central bankers' preference base on what they say rather than how they vote.

Taylor Rule Formula

$$\text{Target Rate} = \text{Neutral Rate} + 0.5 * (GDP_e - GDP_t) + 0.5 * (I_e - I_t)$$



Economics Primer : Taylor's Rule and Monetary Policy

DATA AND METHODOLOGY

- FOMC transcript between 2005 and 2008
- CPI data:http://www.usinflationcalculator.com/inflation/historical-inflation-rates/
- Economic projections from the Greenbook
- FOMC dissent data
- Policy validation data
- Mixed effect GLM (binomial)
  - (Not in scope of this course: LDA: topic modelling)

REPLICATION OBJECTIVE

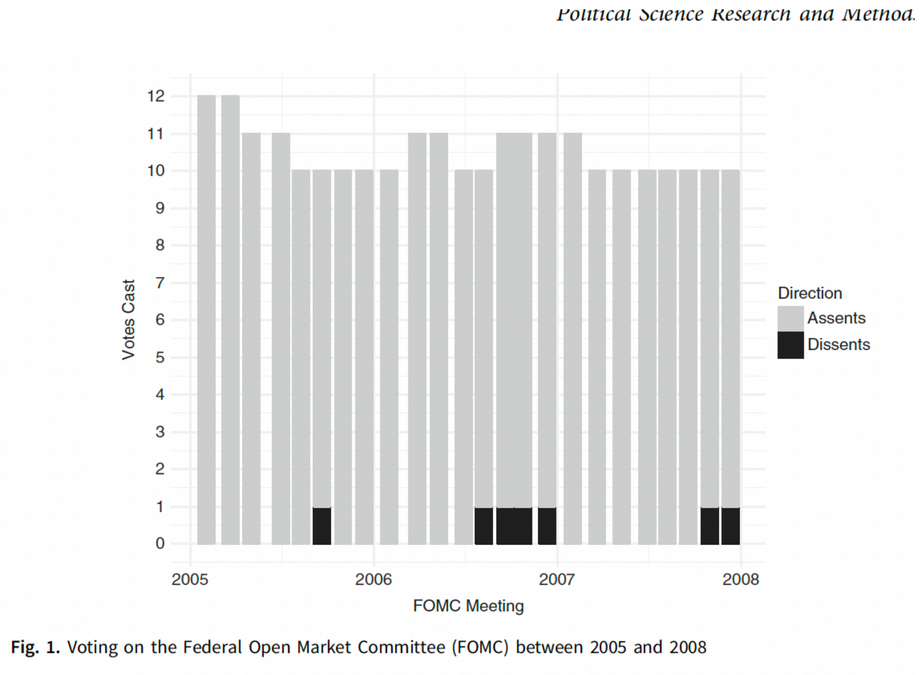


Fig. 1. Voting on the Federal Open Market Committee (FOMC) between 2005 and 2008

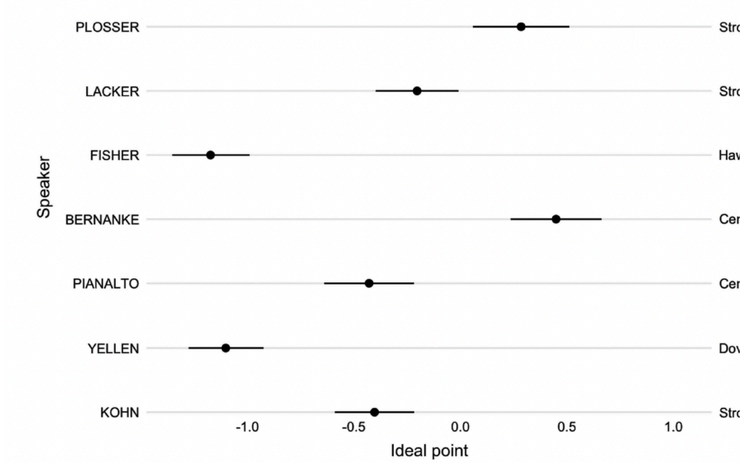


Fig. 3. Comparing estimated fixed ideal points from text with expert placement in *Financial Times*

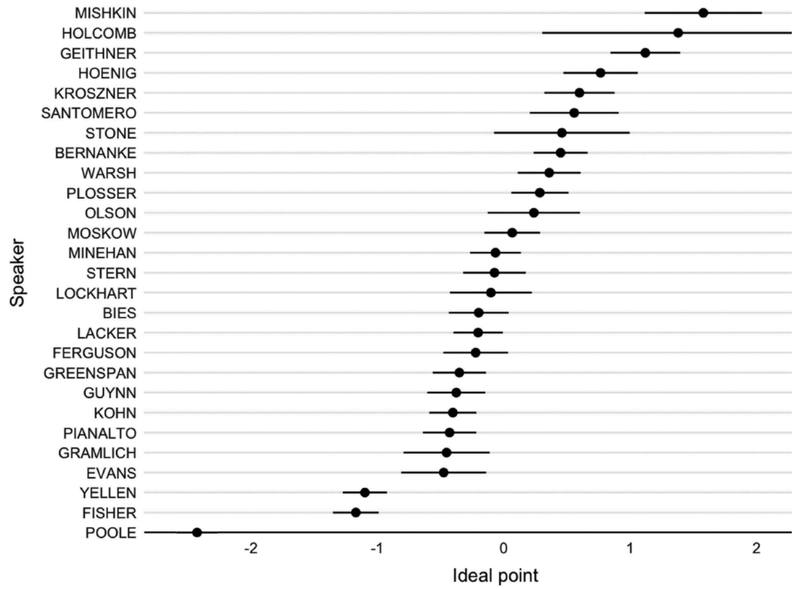


Fig. 2. Estimated fixed ideal points from full transcripts with meeting random effects. Dovish members are those the left hand side of the scale and Hawkish members are those on the right hand side.

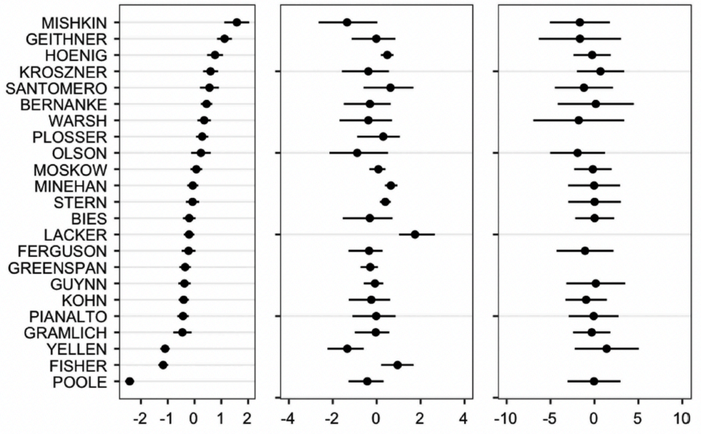


Fig. 4. Comparing ideal points from text, implied voting and preferred interest rate measures. Column (1) estimated preferences from text, column (2) estimated preferences from votes, and column (3) estimated interest rate preferences

REPLICATION OBJECTIVE (CONTINUED)

Table 1. Regression Results for Federal Open Market Committee (FOMC) Bank Presidents and District-Level Economic Information

	Dependent Variable		
	(Inflation/Output and Unemployment)		
	(1)	(2)	(3)
National inflation rate	0.007		
	(−0.010, 0.024)		
Log (non-performing loans)		0.415***	
		(0.314, 0.517)	
National unemployment rate	−0.466***	−0.318***	
	(−0.585, −0.347)	(−0.440, −0.195)	
National inflation 1 year ahead			−0.456***
			(−0.567, −0.344)
National unemployment 1 year ahead			−0.741***
			(−0.992, −0.489)
Difference in regional to national unemployment	−0.253***	−0.245***	−0.371***
	(−0.366, −0.141)	(−0.358, −0.133)	(−0.489, −0.252)
Constant	6.035***	−0.866	8.453***
	(5.338, 6.732)	(−2.680, 0.947)	(7.041, 9.865)
Observations	175	175	175
Log likelihood	−1098.516	−1074.790	−1092.171
Akaike information criterion	2207.032	2159.580	2194.342
Bayesian information criterion	2222.856	2175.404	2210.166

Note: *p < 0.1, **p < 0.05, ***p < 0.01.

Table 2. Predicting Dissents in Policy Rates and Policy Statements with Ideal Points and Voting Status

	Dependent Variable	
	Dissent Policy Rate	Dissent Statement
	(1)	(2)
Ideal point	−0.063	−0.145
	(0.153)	(0.089)
On vote	−0.738*	−0.753***
	(0.404)	(0.243)
Constant	−2.610***	−0.650**
	(0.424)	(0.256)
Observations	405	403
Log likelihood	−100.618	−222.952
Akaike information criterion	209.236	453.904
Bayesian information criterion	225.252	469.900

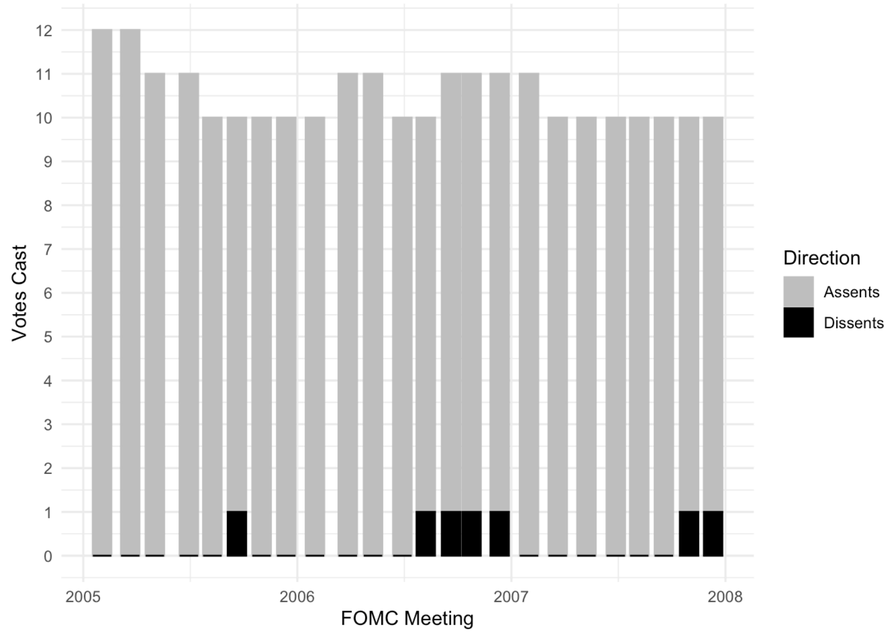
Note: *p < 0.1, **p < 0.05, ***p <0.01.

- *2 models 4 figures 2 table*

MY REPLICATION (1/4)

Figure 1:descriptive plot: member consensus

```
read_excel("FOMC_Dissents_Data.xlsx", skip = 3, col_names = TRUE) %>%
  filter(Year >= 2005, Year <= 2007) %>%
  group_by(`FOMC Meeting`) %>%
  mutate(diss = `Number Presidents Dissenting` + `Number Governors Dissenting`) %>%
  summarise(total = `FOMC Votes`, Assents = total - diss, Dissents = diss) %>%
  gather(Direction, Votes, -c(`FOMC Meeting`, total)) %>%
  ggplot(aes(x = `FOMC Meeting`, y = Votes, colour = Direction, fill = Direction)) +
  geom_bar(stat = "identity") +
  scale_colour_manual(values = c("grey", "black")) +
  scale_fill_manual(values = c("grey", "black")) +
  scale_y_continuous("Votes Cast", breaks = 0:12, labels = as.character(0:12)) +
  theme_minimal()
```



Linear mixed effects model

Models for both the Bank Presidents and also the Board Members

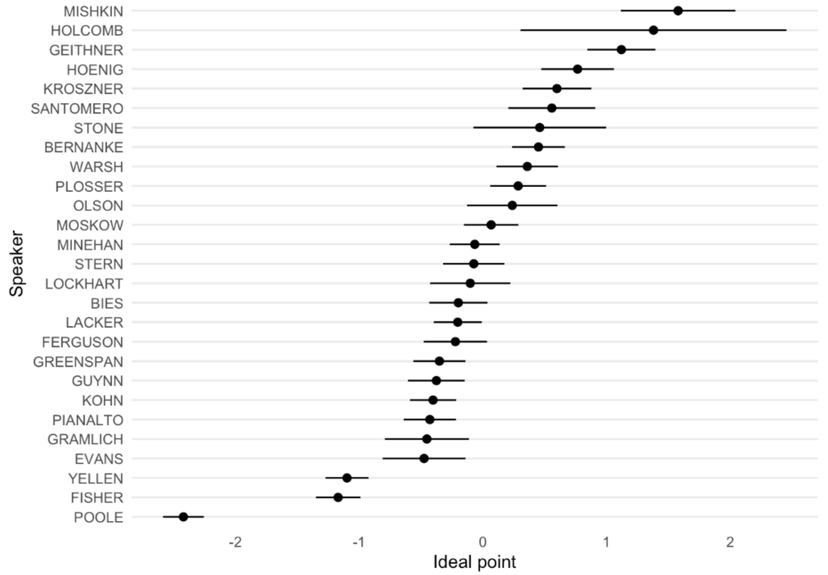
```
mod.mix <- glmer(as.matrix(depvar) ~ (1 | name) + (1 | month),
                 data = meta, family = binomial)
mod.mix
```

```
rf <- ranef(mod.mix, condVar = TRUE)$name
rf_postvar <- as.vector(attr(rf, "postVar"))
df <- data.frame(ideal = rf[[1]]) %>%
  mutate(se = sqrt(rf_postvar),
         upper = ideal + 2 * se,
         lower = ideal - 2 * se,
         speaker = factor(rownames(rf),
                          levels = rownames(rf)[order(ideal)])) %>%
  arrange(ideal)
```

Estimated Fixed Ideal Points from Full Transcripts with meeting random effects.

#Replication result: This is Figure 2 from the paper

```
ipplot(df$ideal, df$speaker, df$lower, df$upper) +
     labs(x = "Ideal point", y = "Speaker")
```

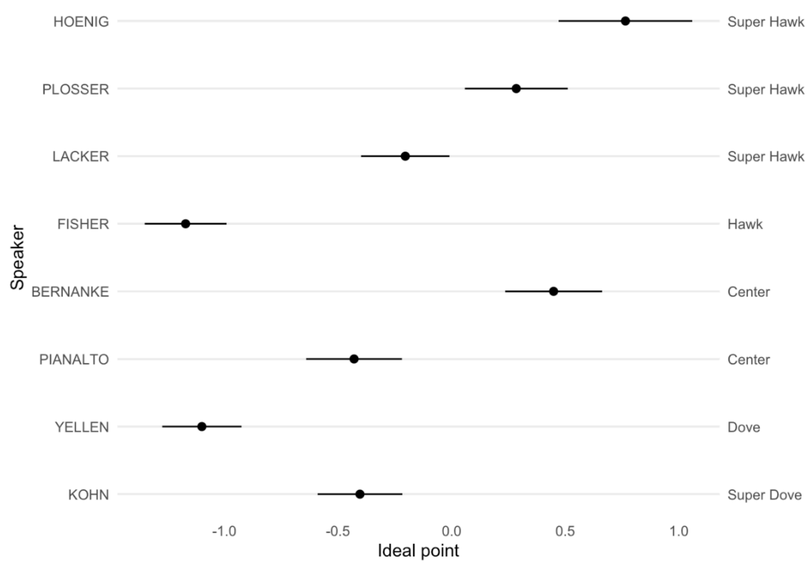


Replicated Fig. 2. Estimated fixed

MY REPLICATION (2/4)

This is Figure 3

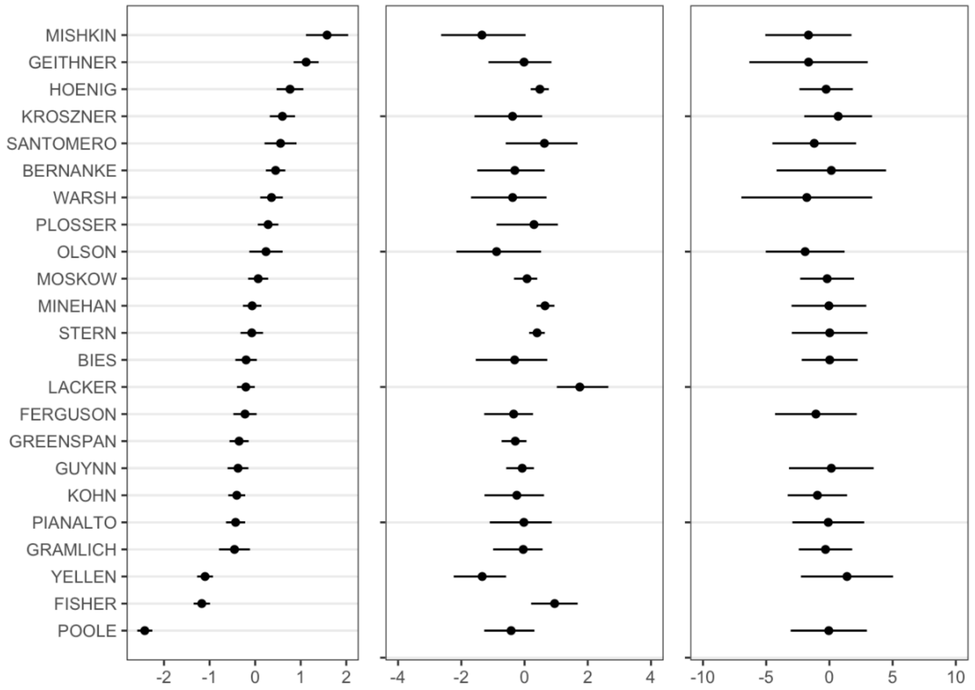
```
labs1 <- small_df$NAME
labs2 <- small_df$coding

ggplot(small_df, aes(x = ideal, y = row)) +
  geom_point(size = 2) +
  geom_segment(aes(x = lower, xend = upper, y = row, yend = row)) +
  scale_y_continuous(breaks = 1:length(labs1),
                     labels = labs1,
                     sec.axis = sec_axis(~.,
                                         breaks = 1:length(labs2),
                                         labels = labs2)) +
  theme_minimal() +
  theme(panel.grid.major.x = element_blank(),
        panel.grid.minor = element_blank(),
        legend.title = element_blank(),
        legend.background = element_blank()) +
   labs(x = "Ideal point", y = "Speaker")
```



This is Figure 4

```
Warning: Removed 4 rows containing missing values (`geom_point()`).
```

```
Warning: Removed 4 rows containing missing values (`geom_errorbarh()`).
```



MY REPLICATION (3/4)

Replicating model 2: adding in the economic covariates

```
regional <- read_excel("GreenbookForecastsRegional.xlsx") %>%
  mutate(reg_un = `Regional Unemployment in Month of Meeting`,
         nat_un = `Projected Unemployment Current`,
         nat_un_q4 = `Projected Unemployment 4-Q AH`,
         nat_inf = `Projected Inflation Current Q CPI`,
         nat_inf2 =  `Projected Inflation Current Q PCE`,
         nat_inf_q42 = `Projected Inflation 4-Q AH PCE`,
         nat_inf_q4 = `Projected Inflation 4-Q AH CPI`,
         diff = nat_un - reg_un,
         logit = log(nat_un / reg_un),
         npl = as.numeric(amount), #non-performing loans
         date = as.Date(Meeting)) %>%
  filter(District != 0)
```

```
Warning: There was 1 warning in `mutate()`.
ℹ In argument: `npl = as.numeric(amount)`.
Caused by warning:
! NAs introduced by coercion
```

1. Model with national inflation + regional (district) unemployment + differennce between national and regional

```
dat <- bind_cols(meta, depvar) %>%
  mutate(date = dmy(date)) %>%
  left_join(regional, ., by = c('name', 'date'))
mod.econ <- glmer(cbind(R, L) ~ (1 | name) + nat_inf + nat_un + diff , data = dat, family = binomial)
```

```
mod.econ2 <- glmer(cbind(R, L) ~ (1 | name) + log(npl) + nat_un + diff, data = dat, family = binomial)
```

```
mod.econ3 <- glmer(cbind(R, L) ~ (1 | name) + nat_inf_q4 + nat_un_q4 + diff,  data = dat, family = bir
```

The source of the CPI data is the Bureau of Labor Statistics http://www.usinflationcalculator.com/inflation/historical-inflation-rates

```
bls_cpi_inflation <- c(2.1,2.4, 2.8,    2.6,    2.7,    2.7,    2.4,    2.0,    2.8,    3.5,    4.3,
5
          4.0,  3.6,    3.4,    3.5,    4.2,    4.3,    4.1,    3.8,    2.1,    1.3,    2.0,    2.5,
          3.0,  3.0,    3.1,    3.5,    2.8,    2.5,    3.2,    3.6,    4.7,    4.3,    3.5,    3.4)
```

Okay, now putting these things into a table, we get the following:

This is Table 1

```
stargazer(mod.econ, mod.econ2, mod.econ3, type="text",
          title="Regression Results for FOMC Bank Presidents", single.row=TRUE,
          ci=TRUE, ci.level=0.9, omit.stat=c("f", "ser"))
```

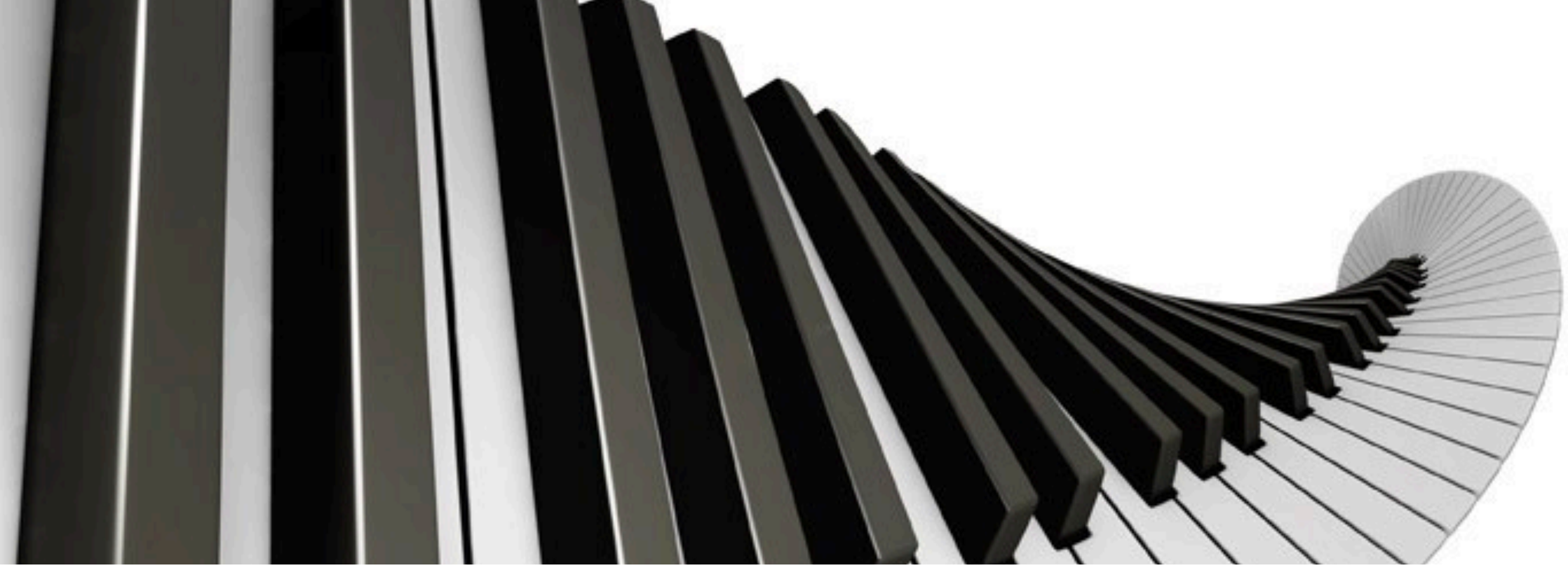
```
Regression Results for FOMC Bank Presidents
=============================================================================================
                                          Dependent variable:
                    ------------------------------------------------------------------------
                                                cbind(R, L)
                              (1)                    (2)                      (3)
---------------------------------------------------------------------------------------------
nat_inf                 0.007 (-0.010, 0.024)
log(npl)                                      0.415*** (0.314, 0.517)
nat_un                -0.466*** (-0.585, -0.347) -0.318*** (-0.440, -0.195)
nat_inf_q4                                                              -0.456*** (-0.567, -0.344)
nat_un_q4                                                               -0.741*** (-0.992, -0.489)
diff                  -0.253*** (-0.366, -0.141) -0.245*** (-0.358, -0.133) -0.371*** (-0.489, -0.252)
Constant               6.035*** (5.338, 6.732)     -0.866 (-2.680, 0.947)    8.453*** (7.041, 9.865)
---------------------------------------------------------------------------------------------
Observations                    175                    175                      175
Log Likelihood               -1,098.516             -1,074.790               -1,092.171
Akaike Inf. Crit.            2,207.032              2,159.580                2,194.342
Bayesian Inf. Crit.          2,222.856              2,175.404                2,210.166
=============================================================================================
Note:                                                                *p<0.1; **p<0.05; ***p<0.01
```

MY REPLICATION (4/4)

This is Table 2

```
stargazer(mod.1, mod.2, type="text", title="Results",
          align=TRUE, dep.var.labels=c("Dissent Policy Rate","Dissent Statement"))
```

```
Results
=============================================================
                              Dependent variable:
                    -----------------------------------------
                    Dissent Policy Rate Dissent Statement
                              (1)                (2)
-------------------------------------------------------------
est                          -0.063             -0.145
                             (0.153)            (0.089)

vote                         -0.738*           -0.753***
                             (0.404)            (0.243)

Constant                    -2.610***          -0.650**
                             (0.424)            (0.256)

-------------------------------------------------------------
Observations                   405                403
Log Likelihood              -100.618           -222.952
Akaike Inf. Crit.            209.236            453.904
Bayesian Inf. Crit.          225.252            469.900
=============================================================
Note:                           *p<0.1; **p<0.05; ***p<0.01
```



ADDING MY TWIST

To the original model: Mixed Effect GLM (binomial/logistic regression)

THE MODEL: GLMM

$$[c_1, c_2] \sim \text{Binomial}(p_i, N), \tag{2}$$

$$p_i = P(c_1 \mid N), \tag{3}$$

$$N = c_1 + c_2. \tag{4}$$

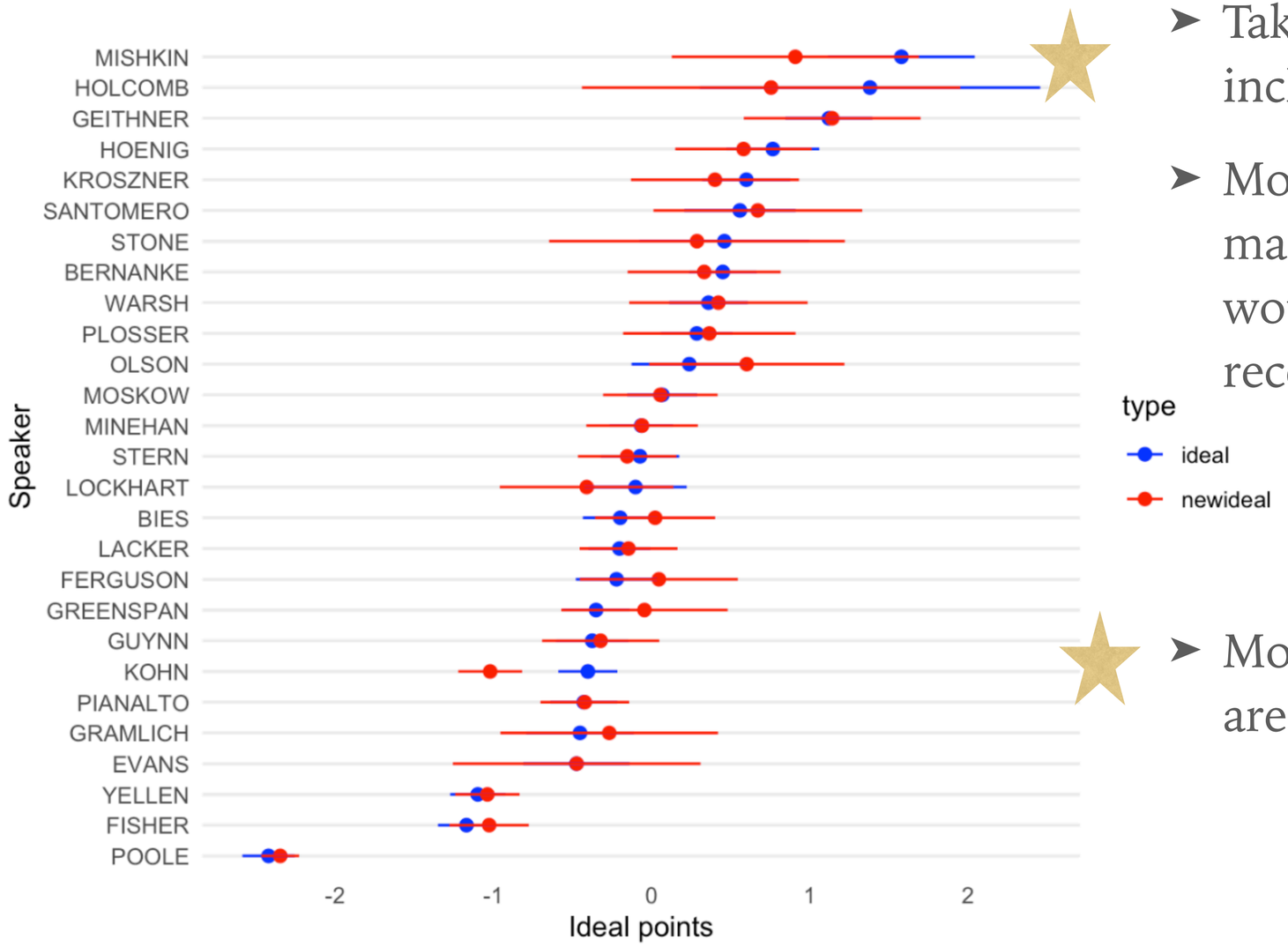
Topics not related to inflation or output can be ignored because they give no information about β_1 / β_2.

Clearly, there are other systematic determinants of the proportion (p_i) of inflation-related speech, so while more elaborate multidimensional models are certainly possible, we limit our attention to the mandated topics as those are the specified parameters in our Taylor rule. In order to account for other (time varying) concerns, we include meeting random effects m_t. We also assume that speakers` positions are exchangeable and model them as draws from a population of committee members. These effects provide our position estimates.

$$\log \frac{p_{i,t}}{1-p_{i,t}} = a + s_i + m_t. \tag{5}$$

(Original model just used month name as random effect variable for meeting, without fixed effect and introduced bugs by not lubridating …)

MY TWIST



- Take into account of all FOMC speech, including the 'neutral' ones.
- Modelling the year as a fixed effect (no matter how hawkish one is, no one would hike if that year the country is in recession!)
- Most results are similar, but the ones that are different, mine model did better :)

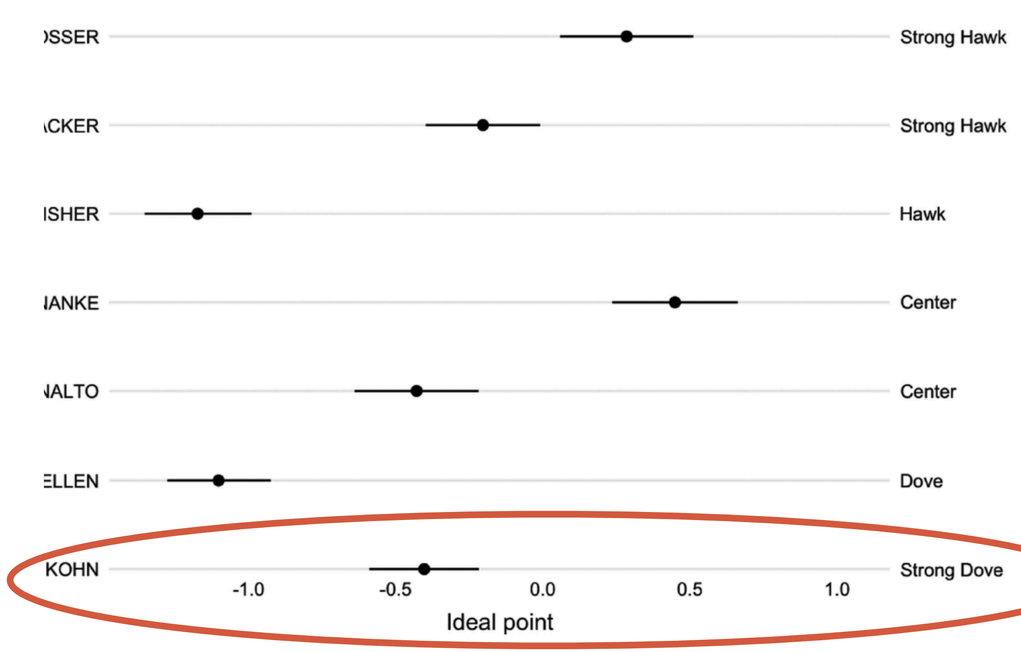
The FOMC's hawk-dove balance

Simone Baribeau MARCH 1 2010

Another dove flies away. Donald Kohn, the Vice Chairman of the federal reserve board, has announced that he will step down come June, leaving the board shy three members.

Mr Kohn is one of the last remaining dove governors. Another dove, Frederic S. Mishkin, resigned in August 2008. The other governor whose seat is still empty is Randall S. Kroszner, who stepped down in January 2009. (Mr Kroszner, who made few comments directly on monetary policy, was no dove: his most remembered statement on rates at the beginning of the financial crisis was unmistakably hawkish).

Left on the board are Ben Bernanke, Elizabeth Duke, and the recently appointed Daniel Tarullo, all centrists, and Kevin Warsh, a moderate hawk. The four rotating voting



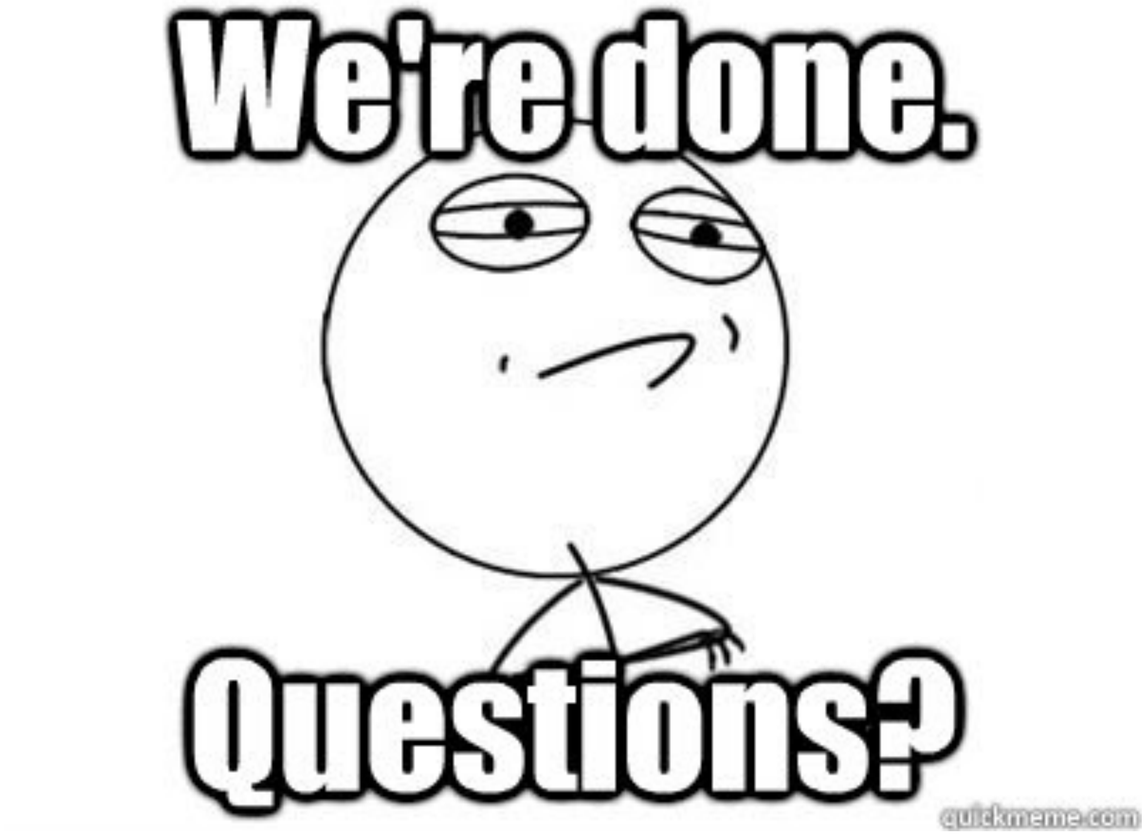
aring estimated fixed ideal points from text with expert placement in *Financial Times*

COMPARING THE MODEL WITH ECONOMIC VARIABLES

Regression Results for FOMC Bank Presidents

	Dependent variable:		
	cbind(R_weight, L_weight)		
	(1)	(2)	(3)
nat_inf	0.026 (-0.017, 0.070)		
log(npl)		0.378** (0.136, 0.620)	
nat_un	-0.581*** (-0.861, -0.301)	-0.419** (-0.711, -0.127)	
nat_inf_q4			-0.364*** (-0.368, -0.359)
nat_un_q4			-0.628*** (-0.632, -0.623)
diff	-0.122 (-0.370, 0.125)	-0.108 (-0.358, 0.142)	-0.188*** (-0.193, -0.184)
Constant	6.515*** (5.100, 7.930)	0.169 (-4.095, 4.434)	7.657*** (7.652, 7.661)
Observations	175	175	175
Log Likelihood	-364.641	-361.689	-367.844
Akaike Inf. Crit.	739.283	733.378	745.688
Bayesian Inf. Crit.	755.107	749.201	761.512
Note:			*p<0.1; **p<0.05; ***p<0.01

(c) the difference between district-level unemployment and national level unemployment in the current-period;


We're done.
Questions?
quickmeme.com