The Turnout Tracker

Jonathan Tannen

sixty-six wards

- A datascience blog about Philadelphia Politics.
- *"FiveThirtyEight for Philadelphia"*
- *www.sixtysixwards.com*

For me the challenges are
- rigor with simplification
- storytelling.

Alternatively: Question formation.
Alternatively 2: The killer plot.

sixty-six wards

- A datascience blog about Philadelphia Politics.
- *“FiveThirtyEight for Philadelphia”*
- www.sixtysixwards.com

Here are Andrew Stober and Kristin Combs’s maps from 2015.

▼ View code

```
library(sf)
divs <- st_read("../../data/gis/2019/Political_Divisions.shp"
  rename(warddiv = DIVISION_N)df_council <- df_council %>%
  group_by(year, election, WARD19, DIV19) %>%
  mutate(pvote = votes/sum(votes))

ggplot(
  divs %>% left_join(
    df_council %>%
      filter(
        year == 2015,
        election=="general",
        CANDIDATE %in% c("ANDREW C STOBER", "KRISTIN COMBS")
      ) %>%
      mutate(warddiv = paste0(WARD19, DIV19), Candidate = for
  )
) +
  geom_sf(aes(fill = 100 *pvote), color=NA) +
  facet_wrap(~Candidate) +
  scale_fill_viridis_c("Percent\nof Votes") +
  theme_map_sixtysix() %+replace%
  theme(legend.position = "right") +
  ggtitle("Third Party votes come from the Wealthy Progressiv
```

Today

Two data visualization stories:

- The Turnout Tracker

- Philadelphia Voting Blocs

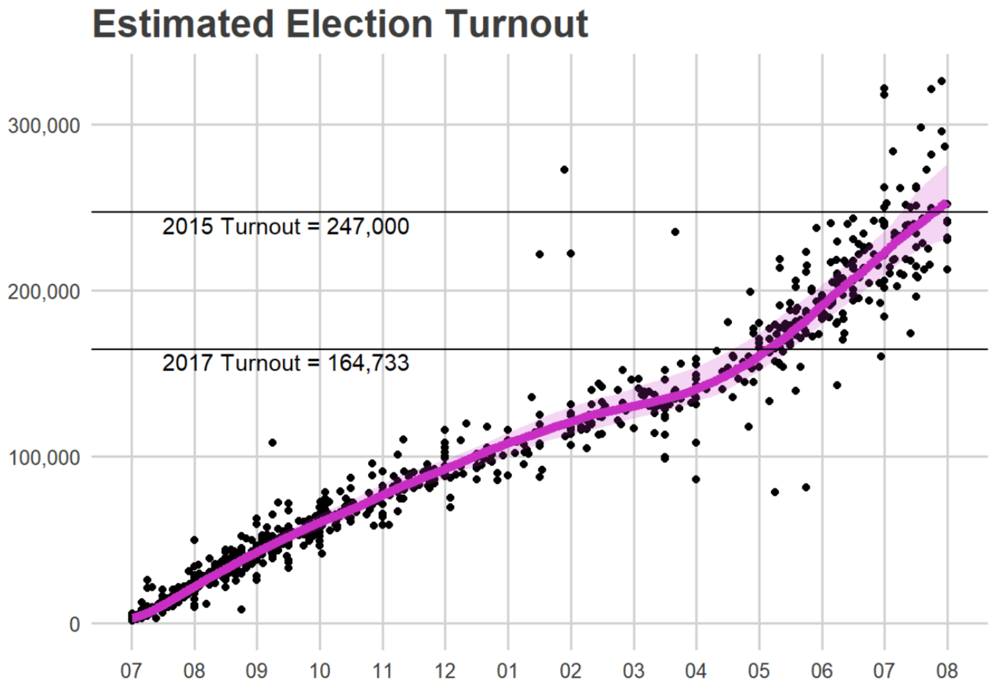
The Turnout Tracker

sixty-six wards

Live 2019 Election Turnout Tracker

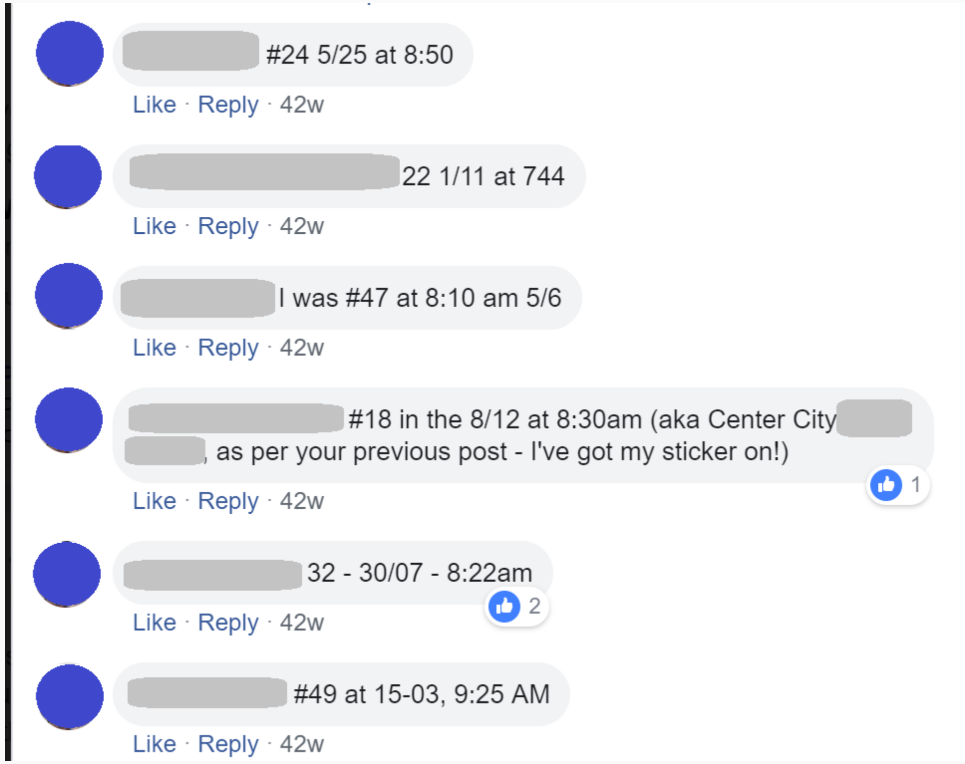
NOTE: This is not an example of expected work for this course.

Live Results

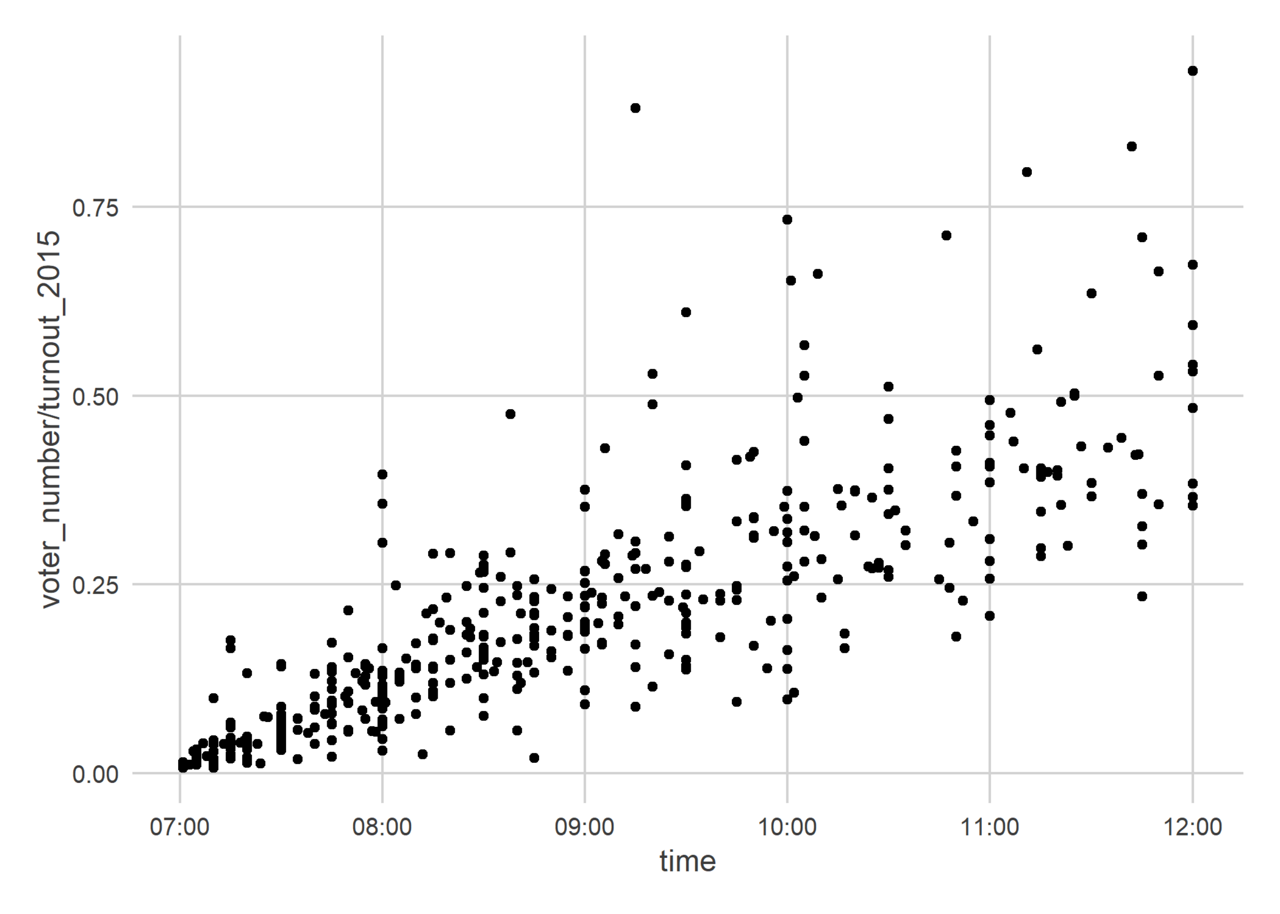


The Turnout Tracker

- If people share where and when they vote in real time, can we predict total turnout?



The Turnout Tracker



The Turnout Tracker

	A	B	C	D	E	F
1	Timestamp	Ward (1 - 66)	Division (1 - 51)	Time of day	Voter number at	I voted...
2	6/1/2020 8:01:58	27	14	9:00:00 AM	215	by mail
3	6/1/2020 8:47:39	2	5	2:22:00 AM	8	by mail
4	6/1/2020 8:48:25	2	5	3:07:00 AM	567	by mail
5	6/1/2020 9:04:45	18	17	12:00:00 PM	69	by mail
6	6/1/2020 9:16:40	18	17	12:00:00 PM	69	by mail
7	6/1/2020 12:27:00	36	35	12:00:00 AM	0	by mail
8	6/1/2020 12:33:32	18	17	6:00:00 PM	2	by mail
9	6/1/2020 13:30:37	27	11	10:00:00 AM	0	by mail
10	6/2/2020 7:32:18	18	10	7:00:00 AM	1	by mail
11	6/2/2020 8:17:07	39	46	7:00:00 AM	1	by mail
12	6/2/2020 8:19:45	60	08	7:22:00 AM	22	by mail
13	6/2/2020 8:25:46	2	24	3:00:00 PM	22	by mail
14	6/2/2020 8:28:30	22	1	4:20:00 PM	69	by mail
15	6/2/2020 8:32:02	14	4	11:00:00 AM	20	by mail
16	6/2/2020 8:32:08	36	2	12:34:00 PM	55378008	by mail
17	6/2/2020 8:35:04	34	30	8:00:00 AM	20	by mail
18	6/2/2020 9:01:06	36	37	4:20:00 PM	255	by mail
19	6/2/2020 9:07:06	27	6	12:00:00 PM	68	by mail

The Turnout Tracker

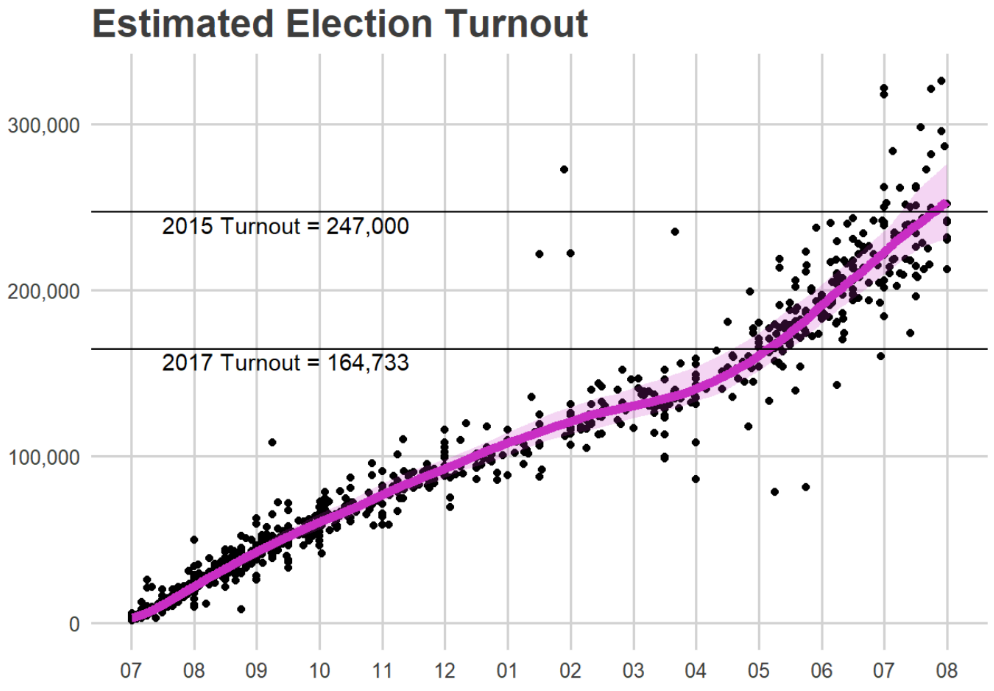
sixty-six wards

Live 2019 Election Turnout Tracker

Welcome to the Sixty-Six Wards turnout tracker! Voters across Philadelphia are sharing their turnout to support citizen science.

> First, vote! Then, share your division and Voter Number at http://bit.ly/sixtysixturnout.

Live Results



A meta view on the nature of this work

Table 1 | A schematic for organizing empirical modelling along two dimensions, representing the different levels of emphasis placed on prediction and explanation

	No intervention or distributional changes	**Under interventions or distributional changes**
Focus on specific features or effects	Quadrant 1: Descriptive modelling Describe situations in the past or present (but neither causal nor predictive)	Quadrant 2: Explanatory modelling Estimate effects of changing a situation (but many effects are small)
Focus on predicting outcomes	Quadrant 3: Predictive modelling Forecast outcomes for similar situations in the future (but can break under changes)	Quadrant 4: Integrative modelling Predict outcomes and estimate effects in as yet unseen situations

From Hofman, J.M., Watts, D.J., Athey, S. *et al.* Integrating explanation and prediction in computational social science. *Nature* **595,** 181–188 (2021).

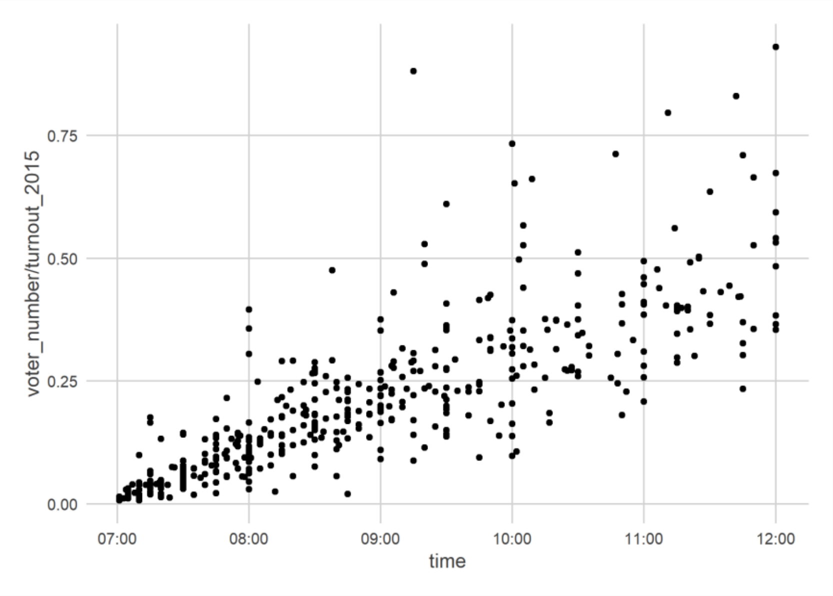
Meta takeaways

- Understanding-focused approach to statistical modeling.
- Practical full-stack problem solving.

A naïve approach

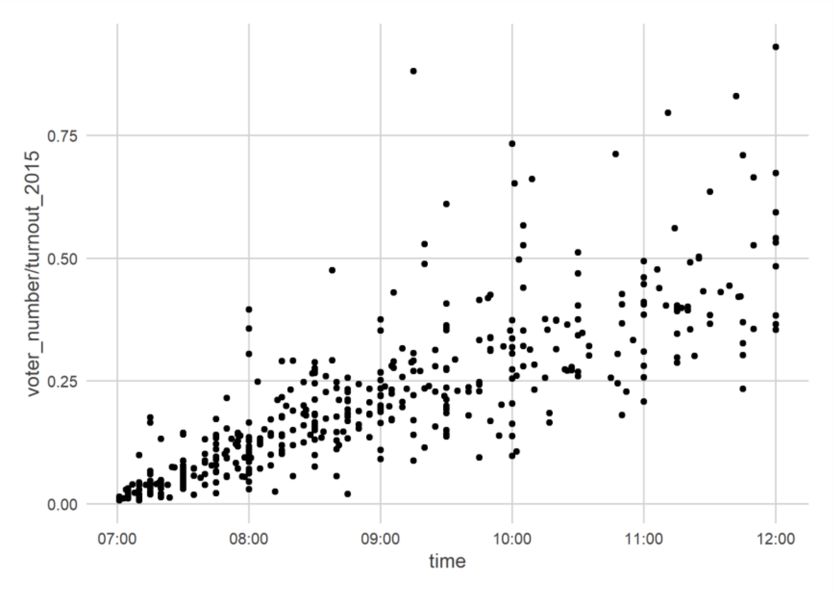
- x_i = response *i*
- t_i = time of response *i*
- d_i = division of response *i*
- T_y = City-wide turnout in year *y*
- $T_{d,y}$ = Final turnout for division *d* in year *y*

$$\hat{T}_{2019} = T_{2015} * avg\left(\frac{x_i}{T_{d_i,2015}} * \frac{13}{t_i}\right)$$



Turnout Tracker: the challenges

- Different divisions have different baseline turnouts.
- Divisions may swing together.
- We don’t know the time pattern.
- There’s *definitely* selection bias into who shares.
- Knowing uncertainty in the estimate is everything.



The solution: $\log(x_i) = \alpha_{y_i} + \mu_{d_i} + \gamma_{d_i y_i} + f(t_i) + e_i$

Turnout Tracker: the model

At time t in division d, year y the voter number x_i so far is

$$\log(x_i) = \alpha_{y_i} + \mu_{d_i} + \gamma_{d_i y_i} + f(t_i) + e_i$$

Turnout Tracker: the model

At time t in division d, year y the number of votes v_{ytd} so far is

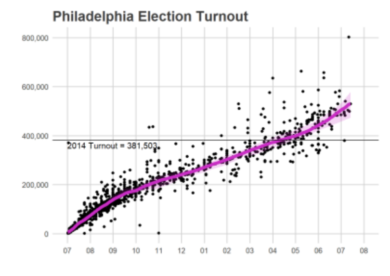
$$\log(x_i) = \alpha_{y_i} + \mu_{d_i} + \gamma_{d_i y_i} + f(t_i) + e_i$$

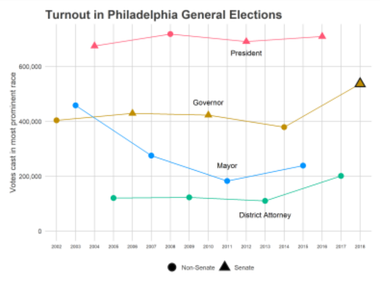
Overall turnout for this year

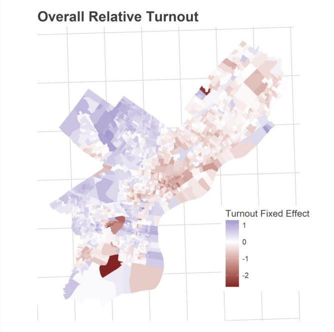
Usual turnout for this division

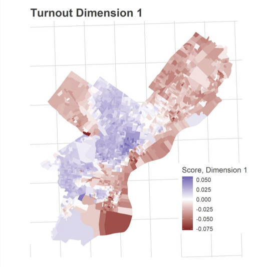
This year's "swing" for the division

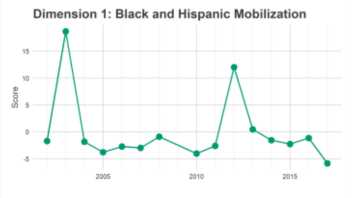
Time pattern









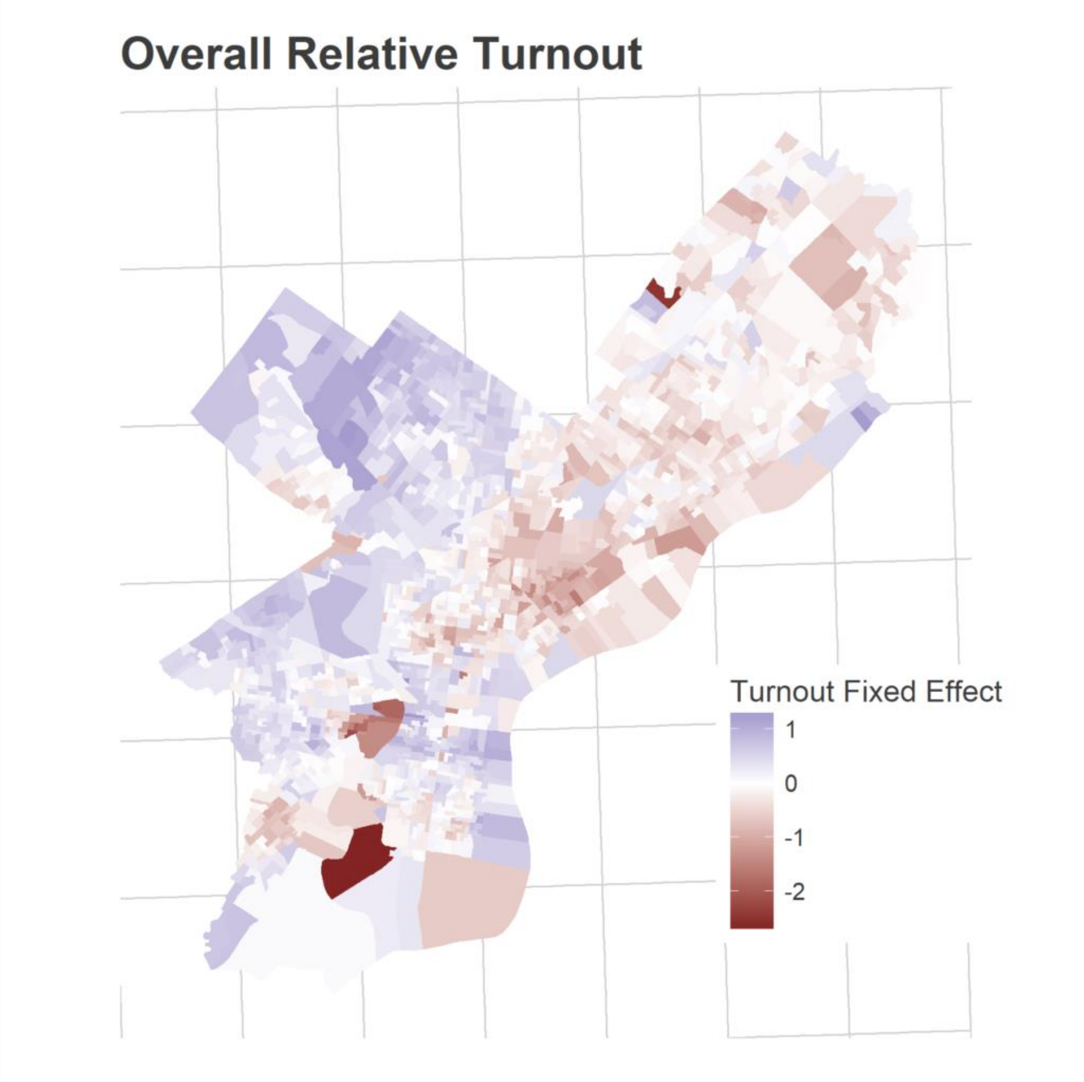


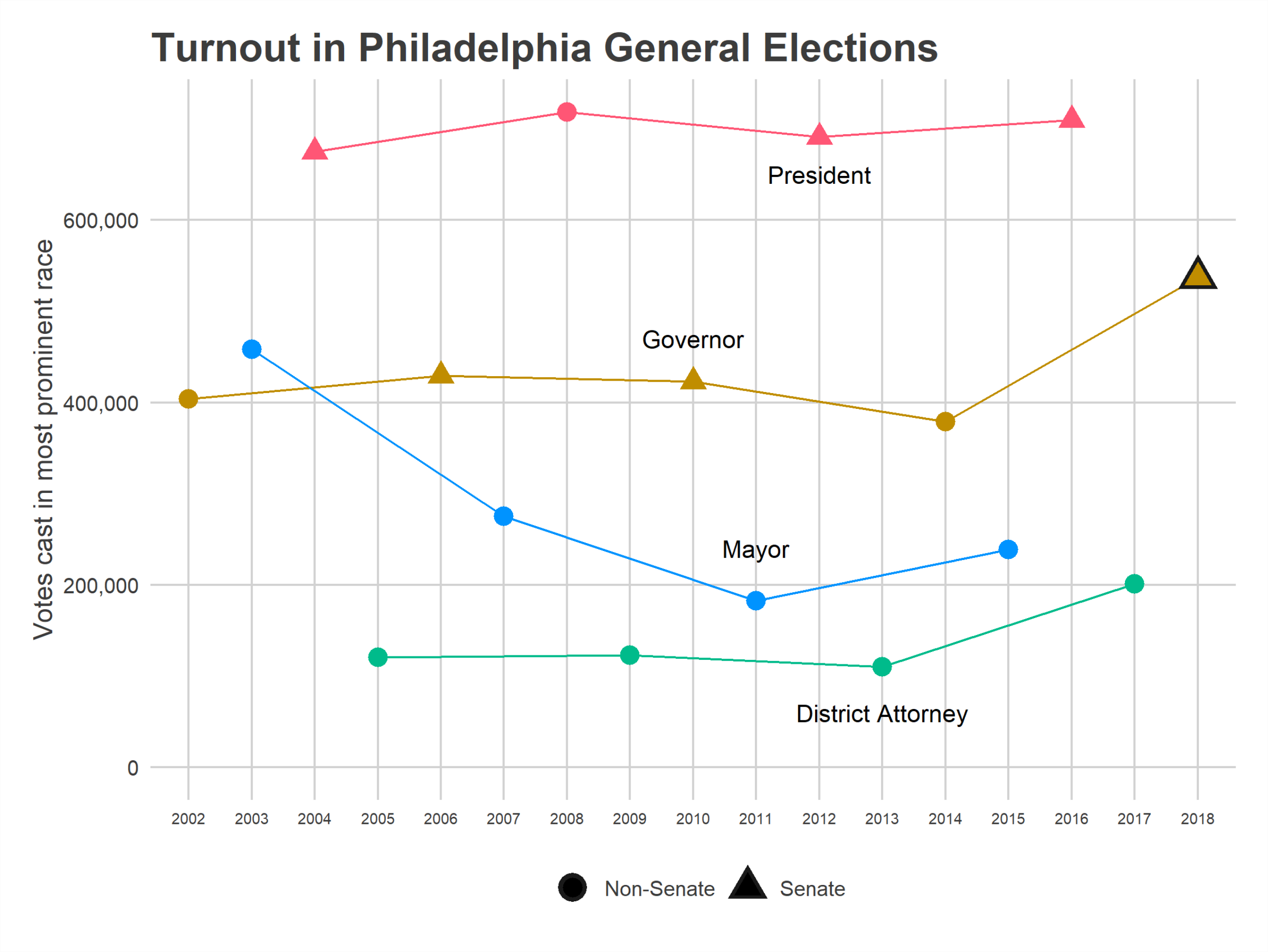
Estimating turnout

$$\log(x_i) = \alpha_{y_i} + \mu_{d_i} + \gamma_{d_i y_i} + f(t_i) + e_i$$

- We can estimate μ_{d_i} from historic data.
- $\gamma_{d_i y_i}$ needs to allow divisions to covary.
  - Model it as $\gamma_{d_i y_i} \sim N(0, \Sigma)$
  - Can estimate Σ from historic data.
- $\alpha_{y_i} + f(t_i)$ need to be estimated in real time.

Estimating Turnout: Baseline Levels μ





Estimating Turnout: Correlated Districts

Singular Value Decomposition

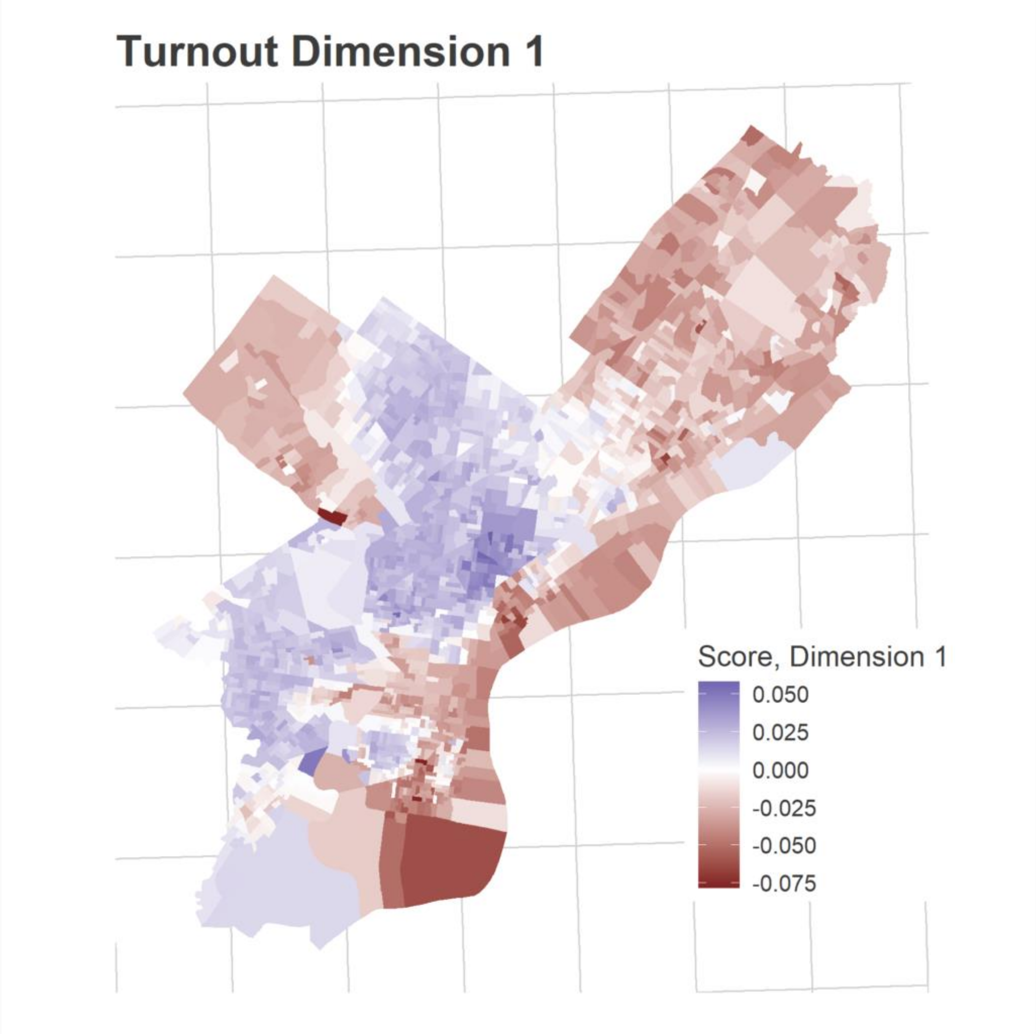
We are interested in a giant D x D matrix of how all divisions correlate with each other. This would require more than 1,703 elections.

Instead, find an approximation using "dimension reduction". (Note: I do this for the D x E matrix of Divisions to Elections).

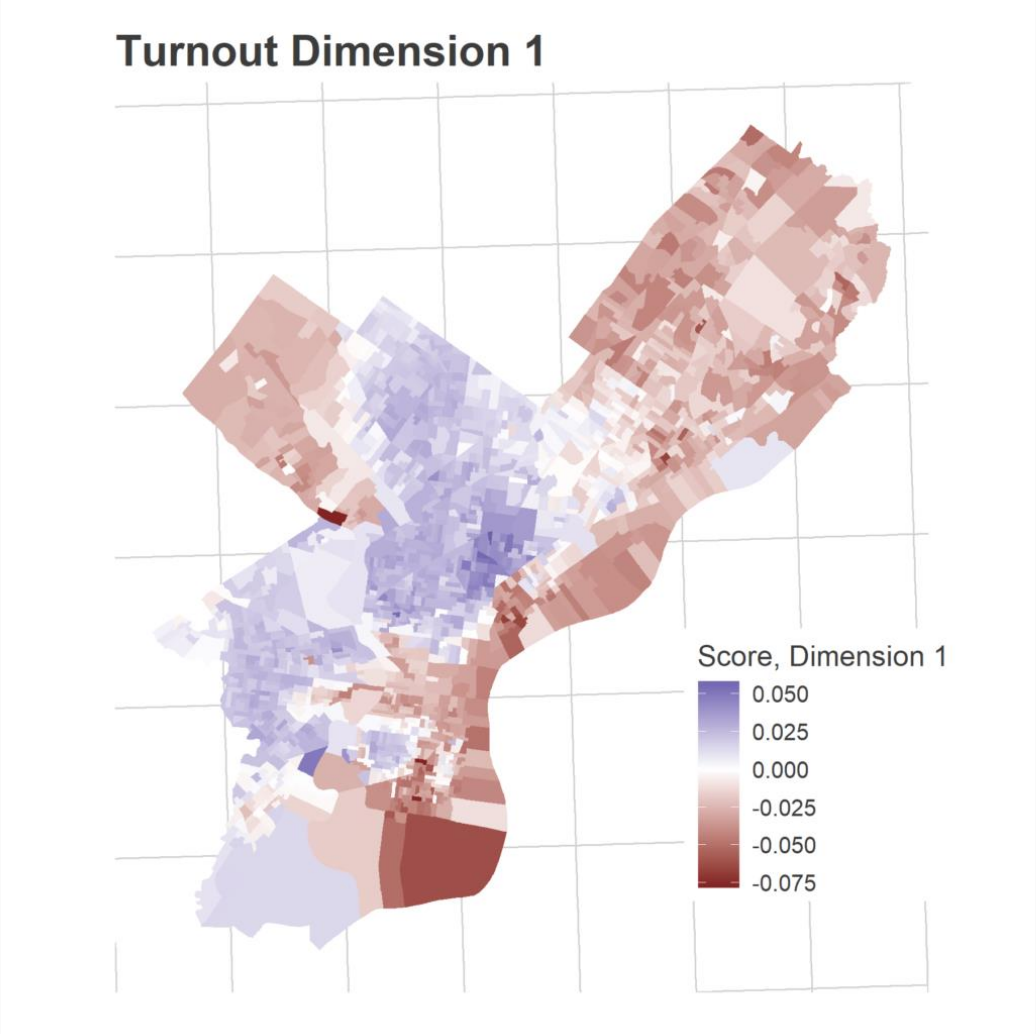
Σ = U' D V

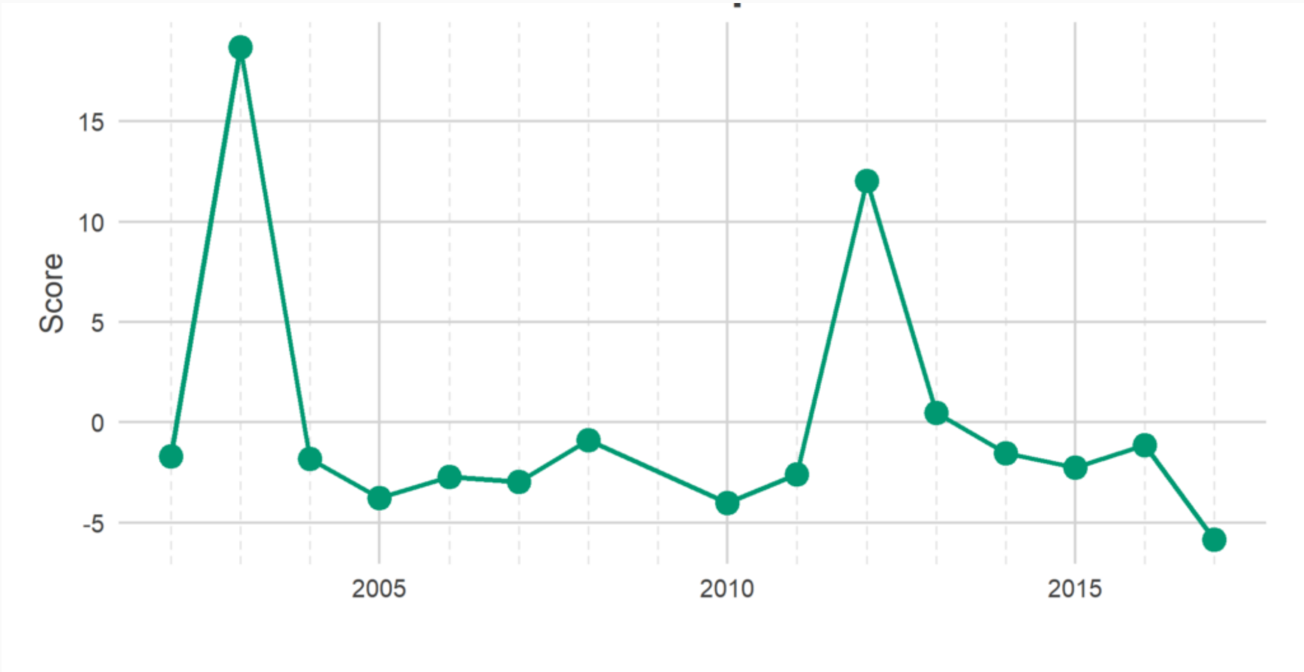
$$\begin{vmatrix} \Sigma_{11} & \Sigma_{12} & \Sigma_{13} \\ \Sigma_{21} & \Sigma_{22} & \Sigma_{23} \\ \Sigma_{31} & \Sigma_{32} & \Sigma_{33} \\ \Sigma_{41} & \Sigma_{42} & \Sigma_{43} \end{vmatrix} = \begin{vmatrix} U_{11} & U_{12} \\ U_{21} & U_{22} \\ U_{31} & U_{32} \\ U_{41} & U_{42} \end{vmatrix} \begin{vmatrix} D_1 & 0 \\ 0 & D_2 \end{vmatrix} \begin{vmatrix} V_{11} & V_{12} & V_{13} \\ V_{21} & V_{22} & V_{23} \end{vmatrix}$$

Estimating Turnout: Correlated Districts

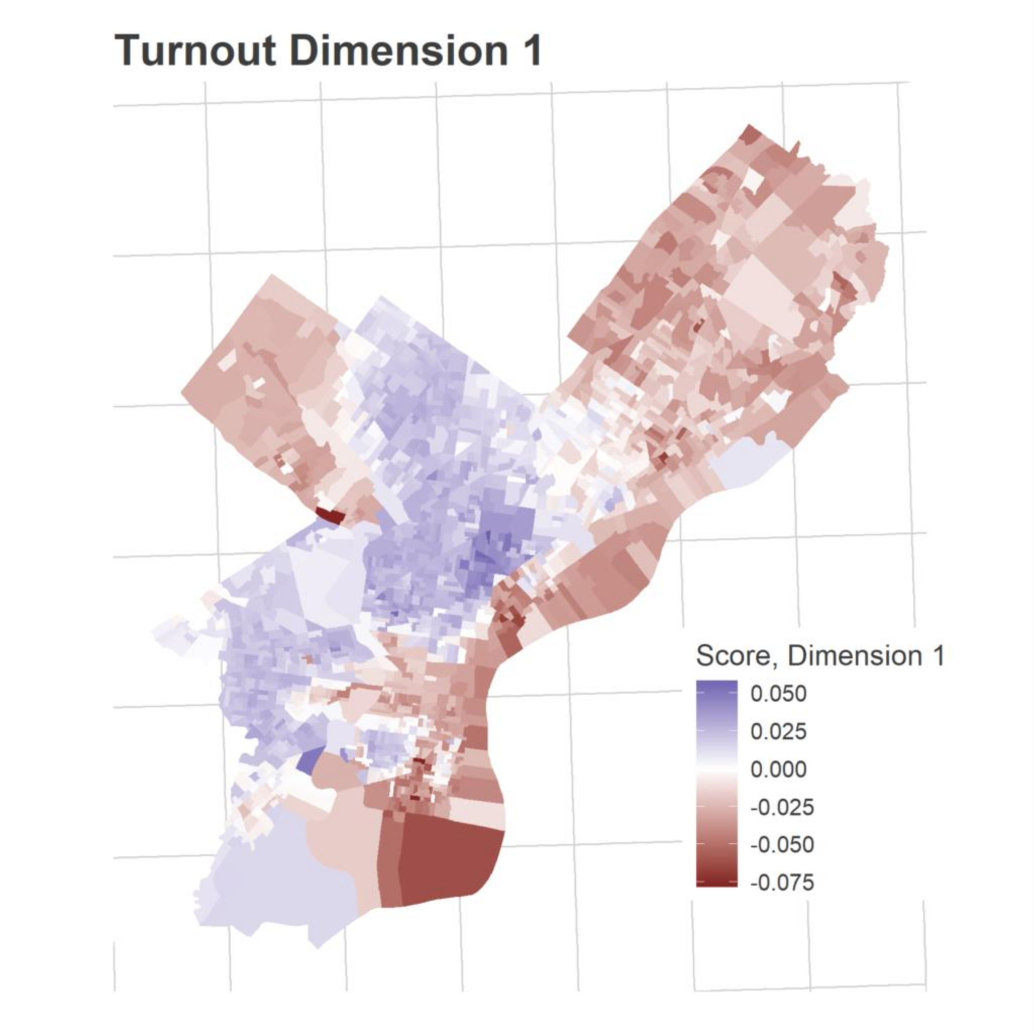


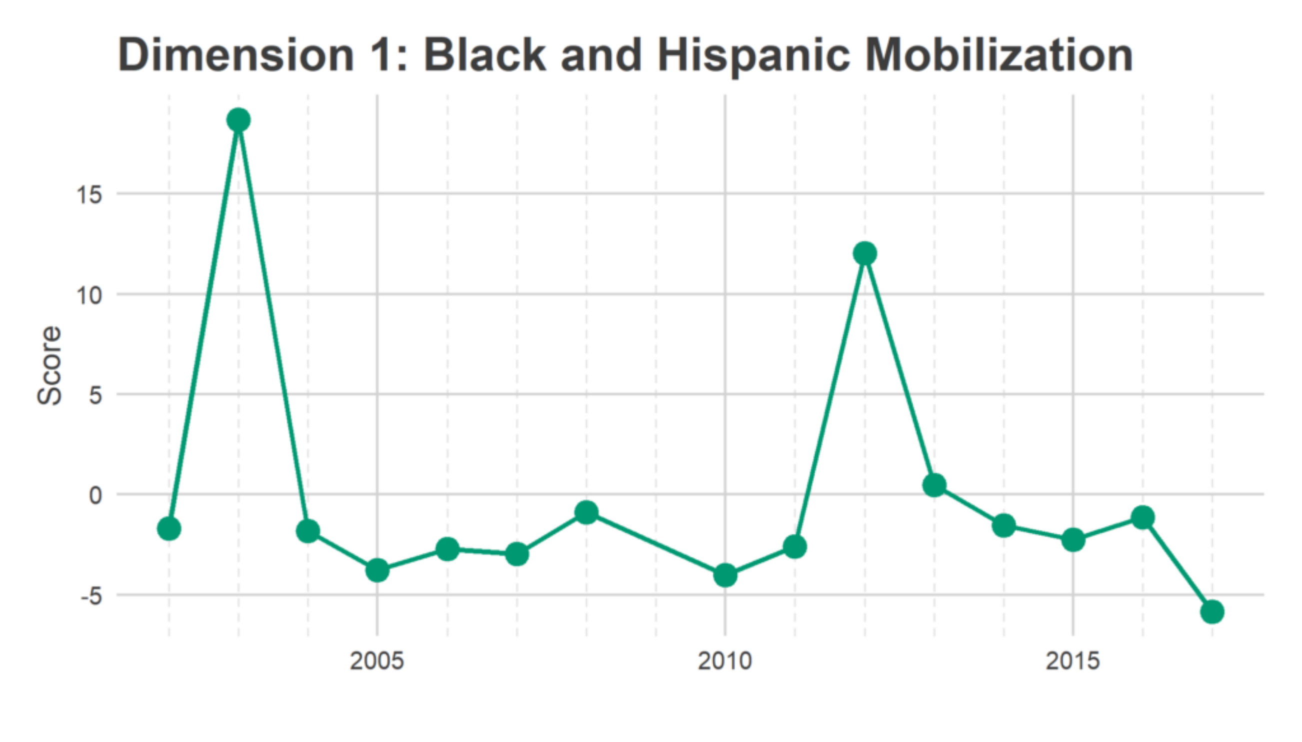
Estimating Turnout: Correlated Districts



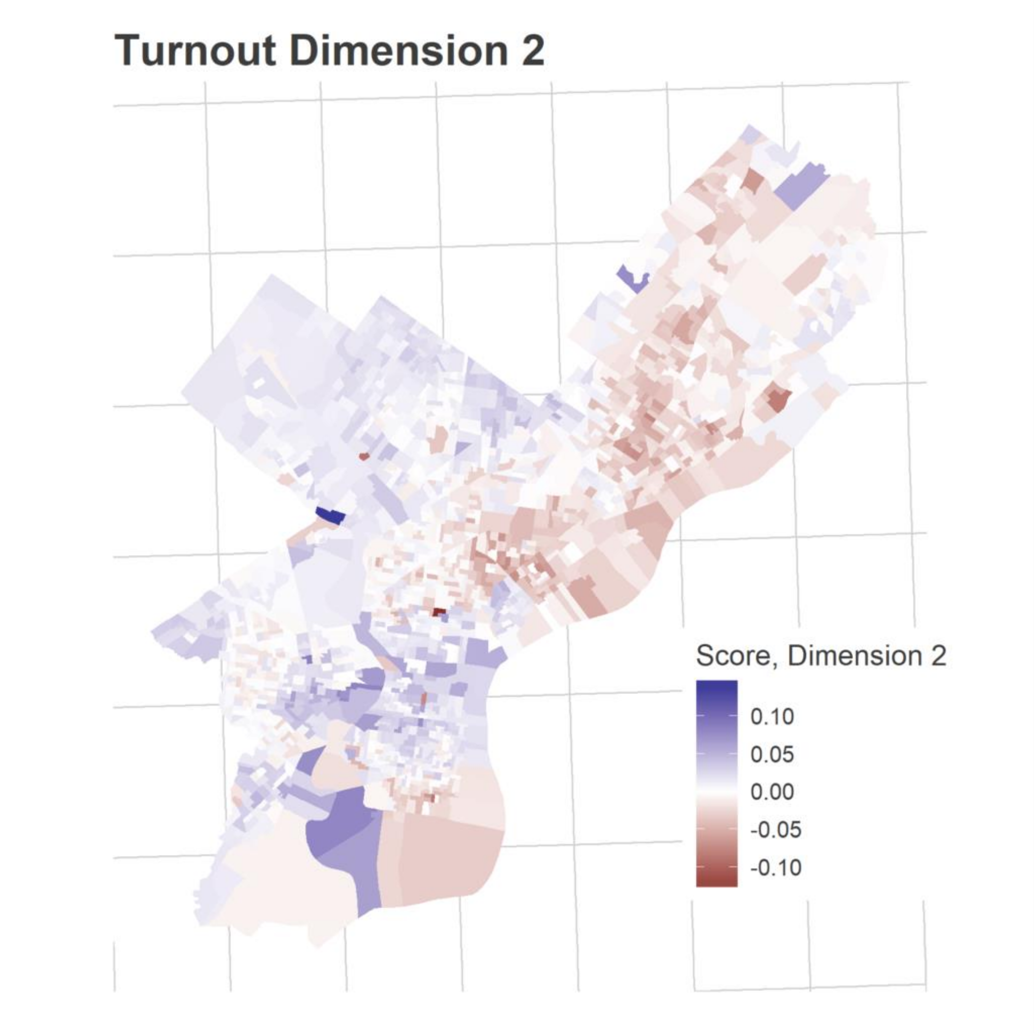


Estimating Turnout: Correlated Districts

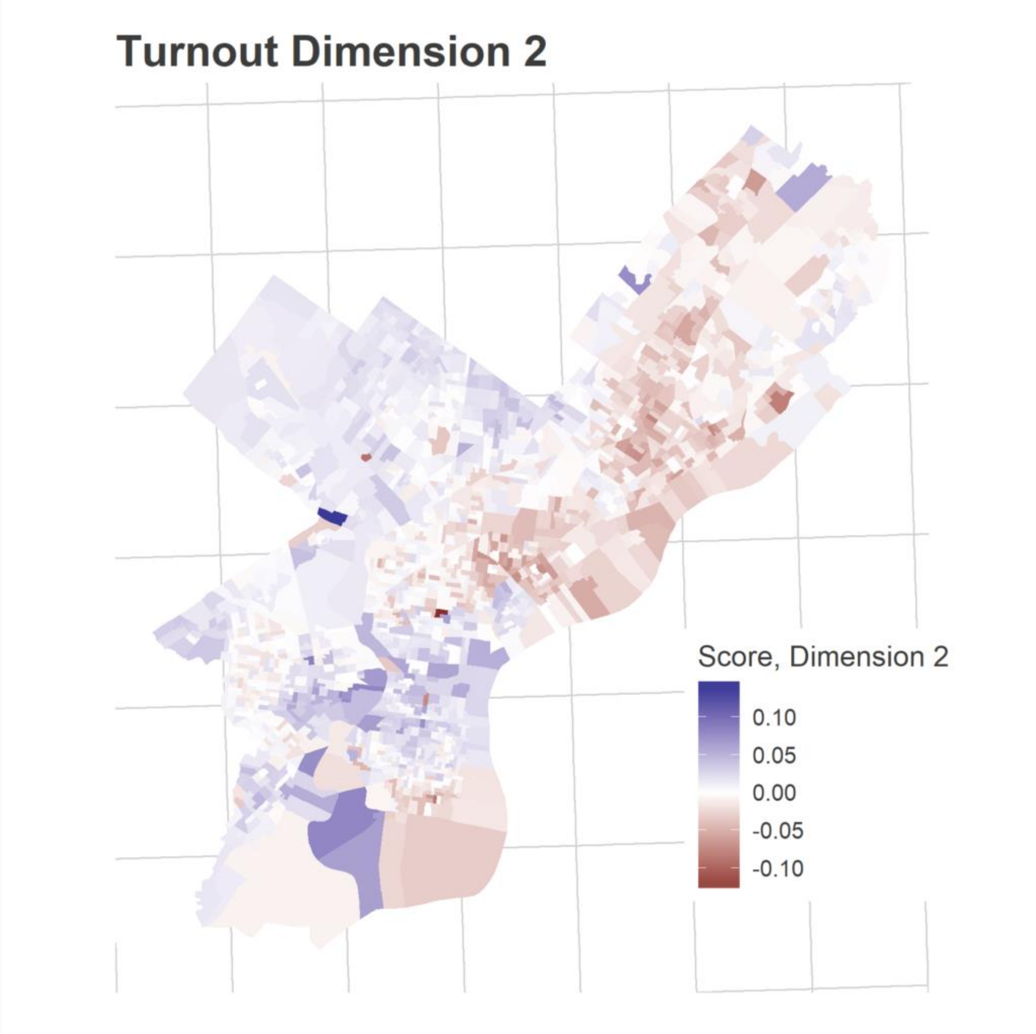


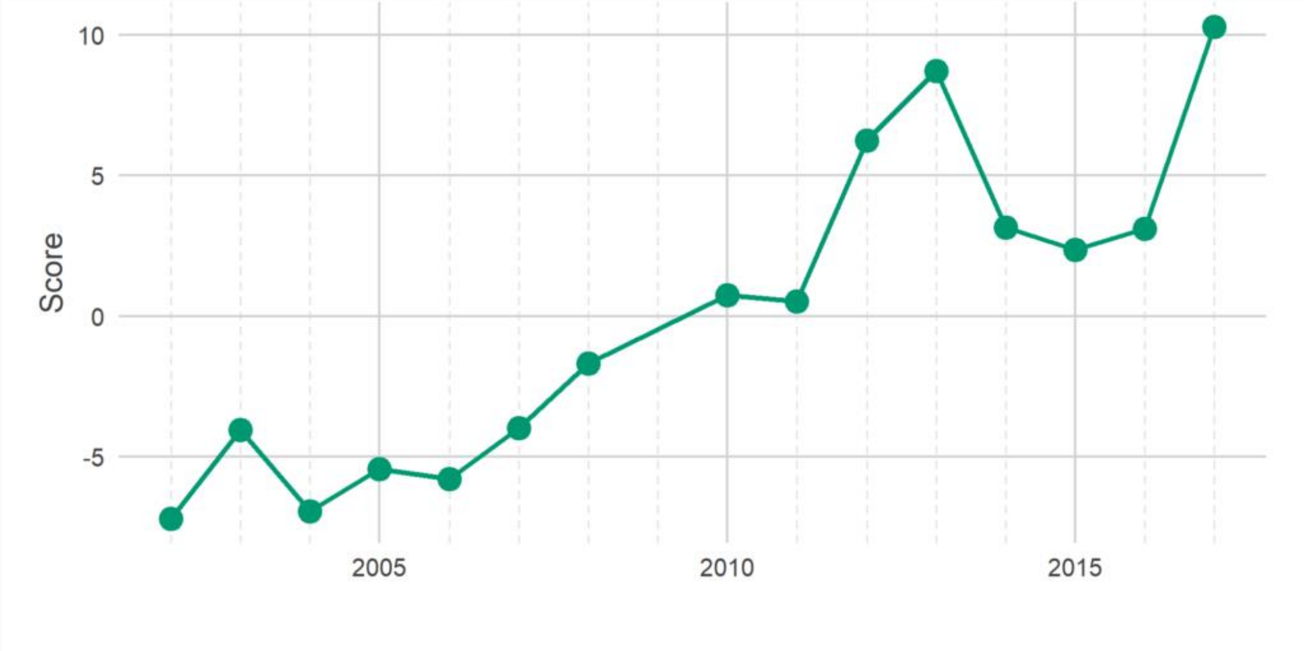


Estimating Turnout: Correlated Districts

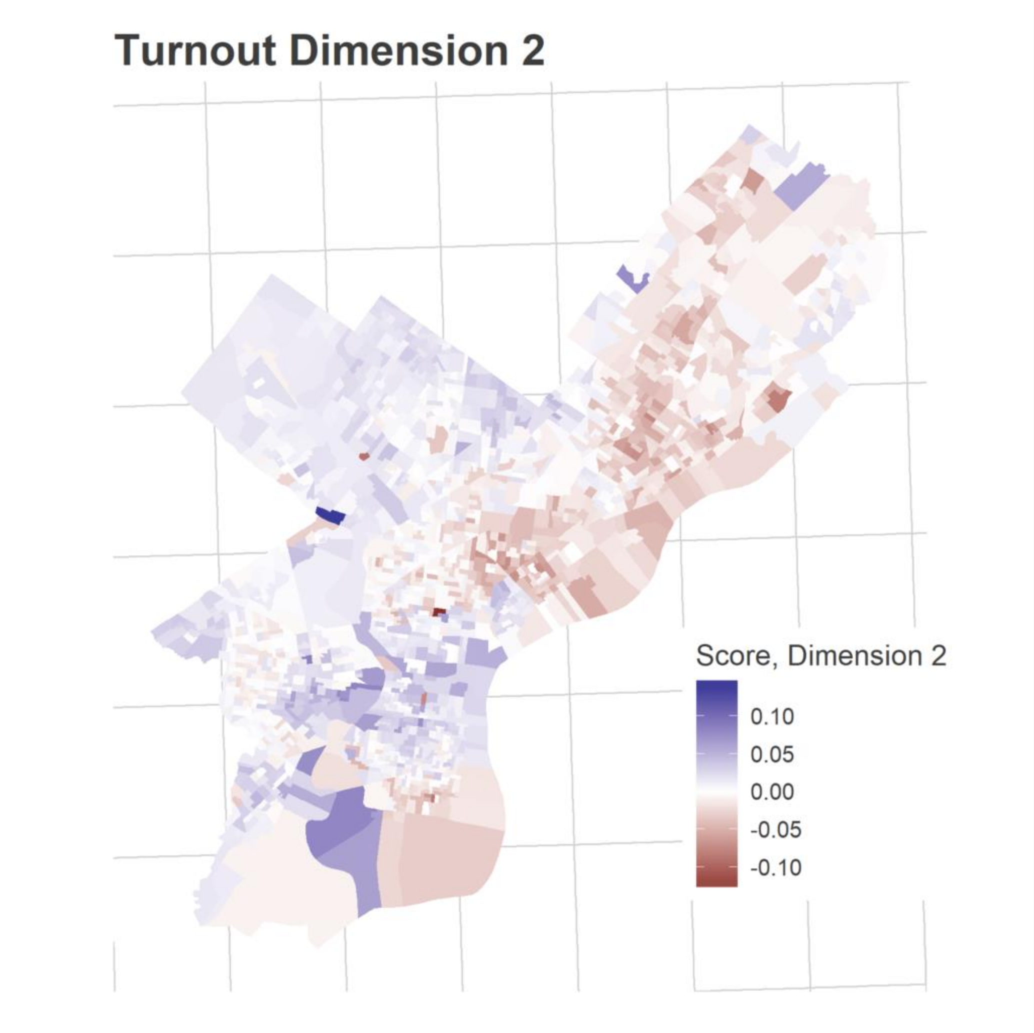


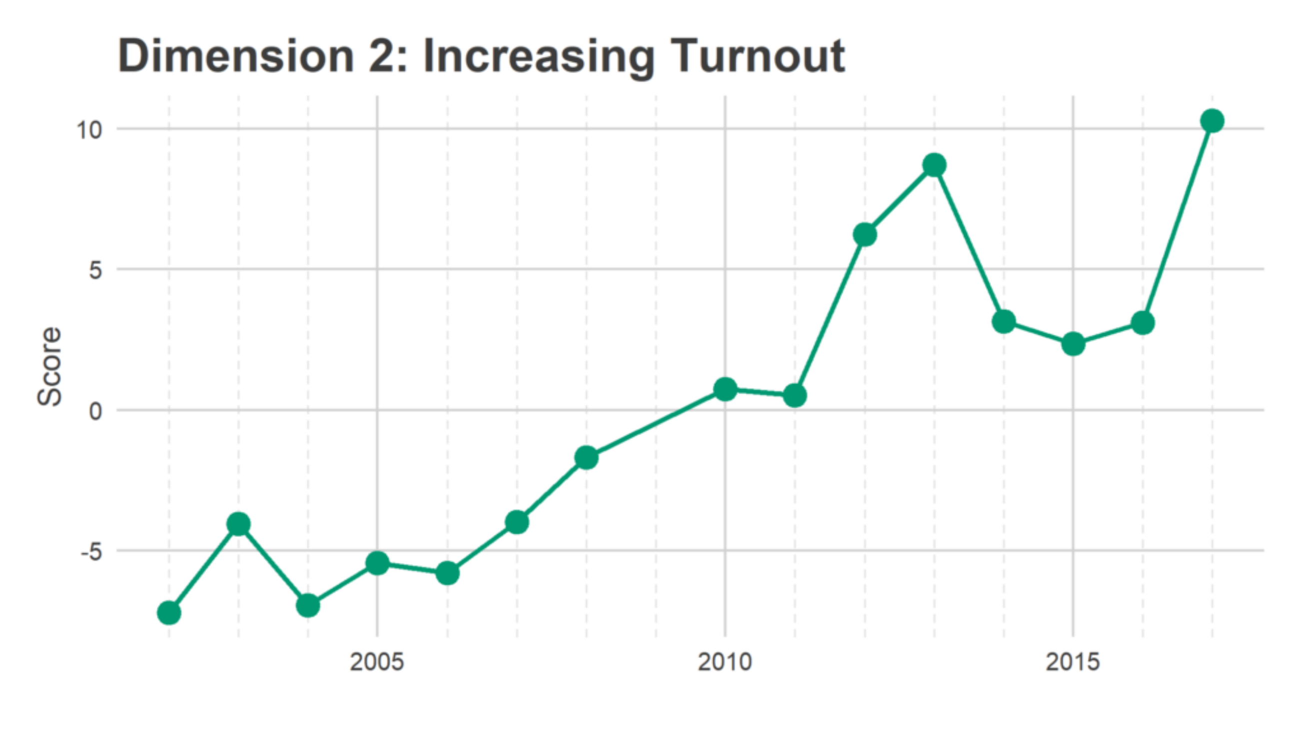
Estimating Turnout: Correlated Districts





Estimating Turnout: Correlated Districts





Estimating Turnout: Time Pattern

Even after we've adjusted for (a) each division's baseline turnout and (b) covarying swings, how do we compare data at 8am with data from 2pm?

$$\log(x_i) = \alpha_y + \mu_d + \gamma_{dy} + f(t) + e_i$$

Estimating Turnout: Time Pattern

Even after we've adjusted for (a) each division's baseline turnout and (b) covarying swings, how do we compare data at 8am with data from 2pm?

$$\log(x_i) = \alpha_y + \mu_d + \gamma_{dy} + f(t) + e_i$$

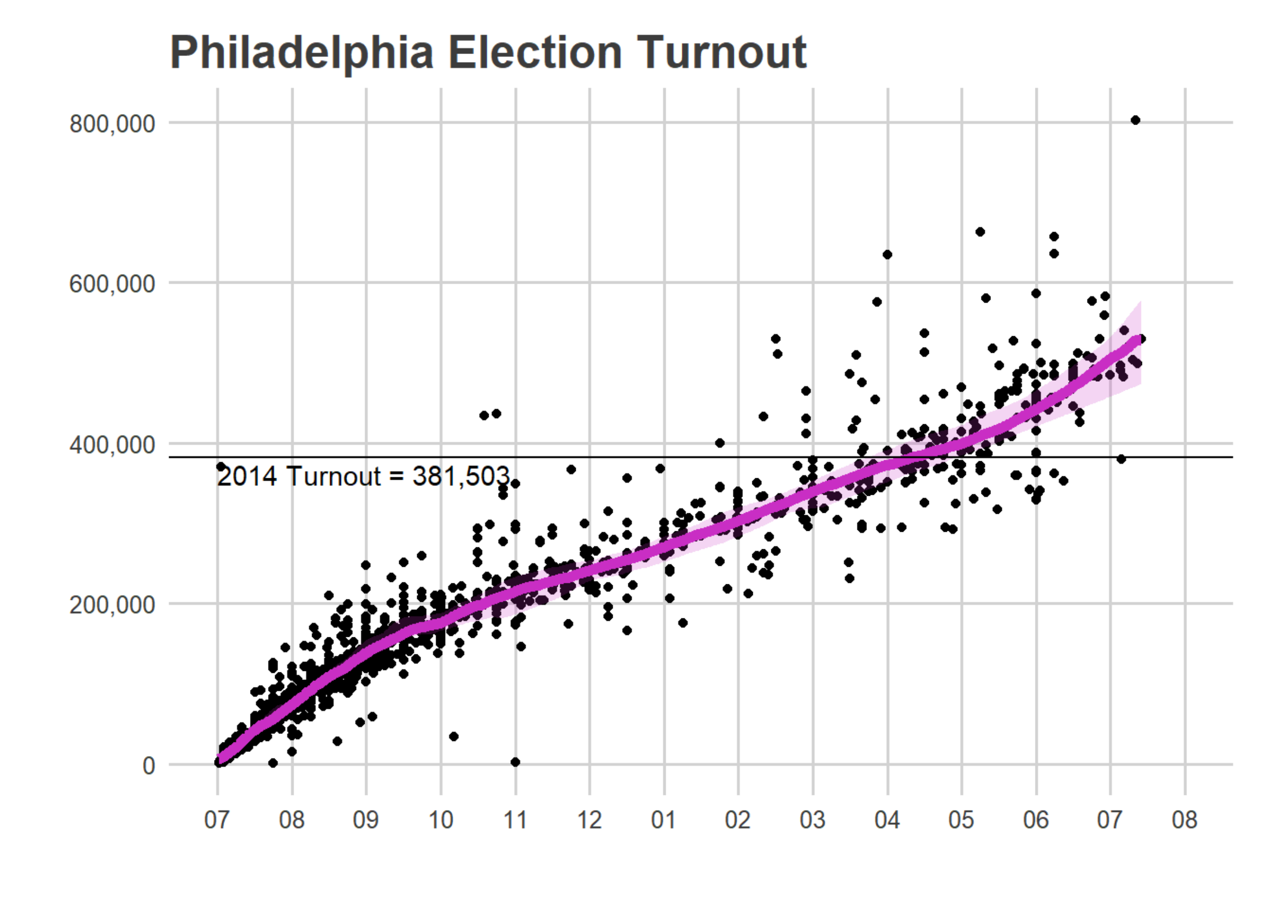
$$\alpha_y + f(t) = E[\log(x_i)] - \mu_d - \gamma_{dy}$$

Estimating Turnout: Time Pattern

Even after we've adjusted for (a) each division's baseline turnout and (b) covarying swings, how do we compare data at 8am with data from 2pm?

$$\log(x_i) = \alpha_y + \mu_d + \gamma_{dy} + f(t)$$

$$\alpha_y + f(t) = E[\log(x_i)] - \mu_d - \gamma_{dy}$$



Two ways to fit the model

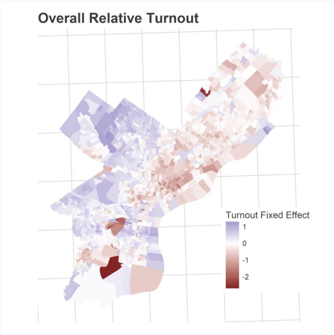
$$\log(x_i) = \alpha_y + \mu_d + \gamma_{dy} + f(t) + e_i$$

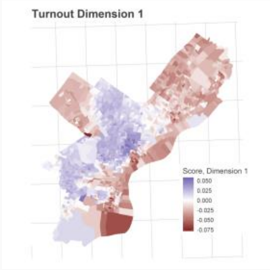
- Iteratively fit random effects γ_{dy} and time effects $\alpha_y + f(t)$.
  - Maximum Likelihood approach. γ_{dy} has closed form solution. Use loess smoother for $\alpha_y + f(t)$.
- Model $f(t)$ as a Gaussian Process, so everything is a conditional normal.

Turnout Tracker: the challenges

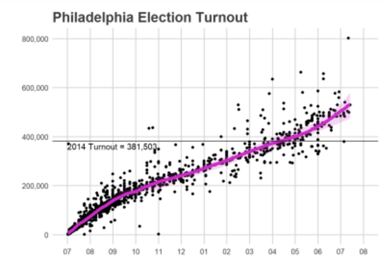
- Different divisions have different baseline turnouts.
- Divisions may swing together.
- We don’t know the time pattern.
- There’s *definitely* selection bias into who shares.
- Knowing uncertainty in the estimate is everything.

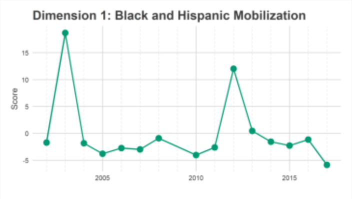
Turnout Tracker: the challenges





- Different divisions have different turnouts.
  - Use each division's baseline rate from past elections.
- Divisions may swing together.
  - Estimate the covariance in divisions' swings from election to election.
- We don't know the time pattern.
  - Estimate it on the fly. 😎



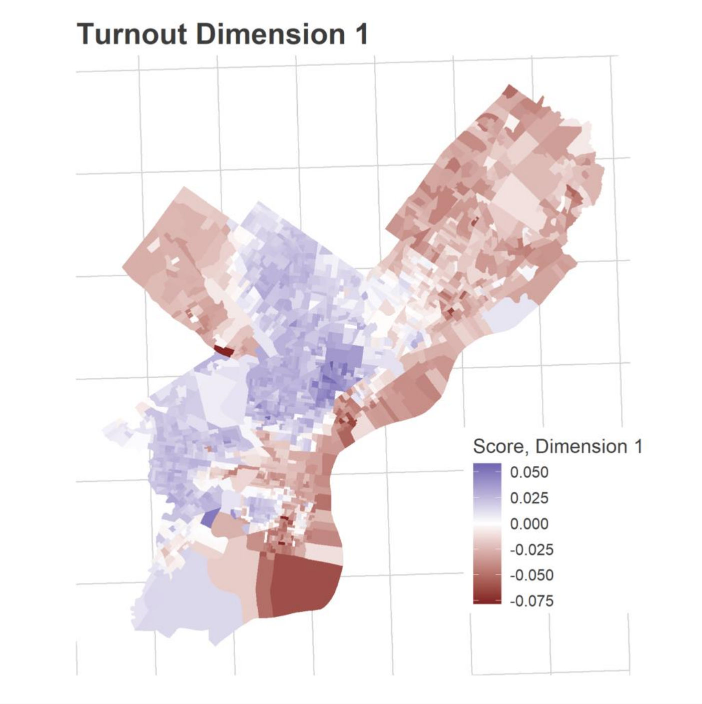


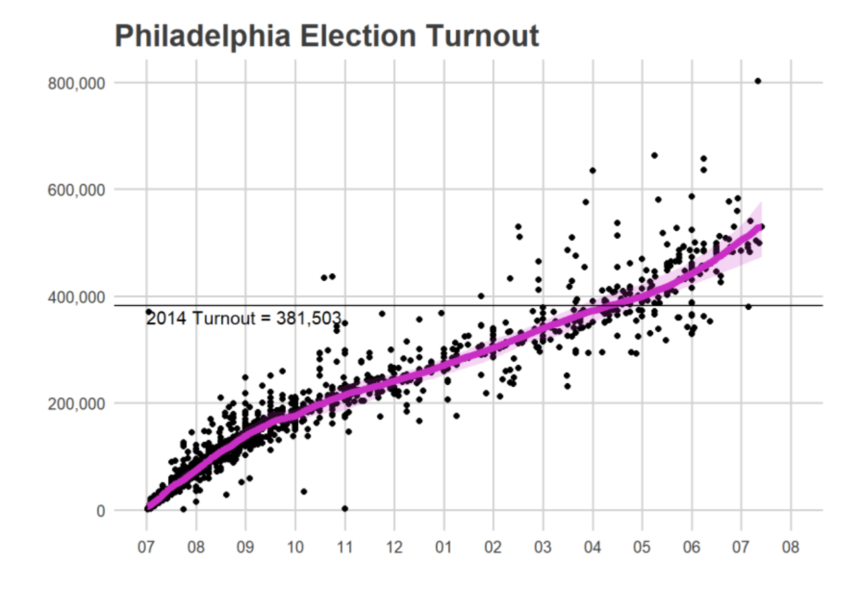
- There's *definitely* selection bias into who shares.
  - oof.
- Knowing uncertainty in the estimate is everything. *???*

Selection bias & Uncertainty

- If selection is only correlated with γ_d, we're safe.
- Use bootstrapping to generate uncertainty.

- How do we know if this works?
  - Integration Tests!





Integration/Back Tests

- Test full runs of the package on known results.
- Tests for
  - Composition errors
  - Correctness errors

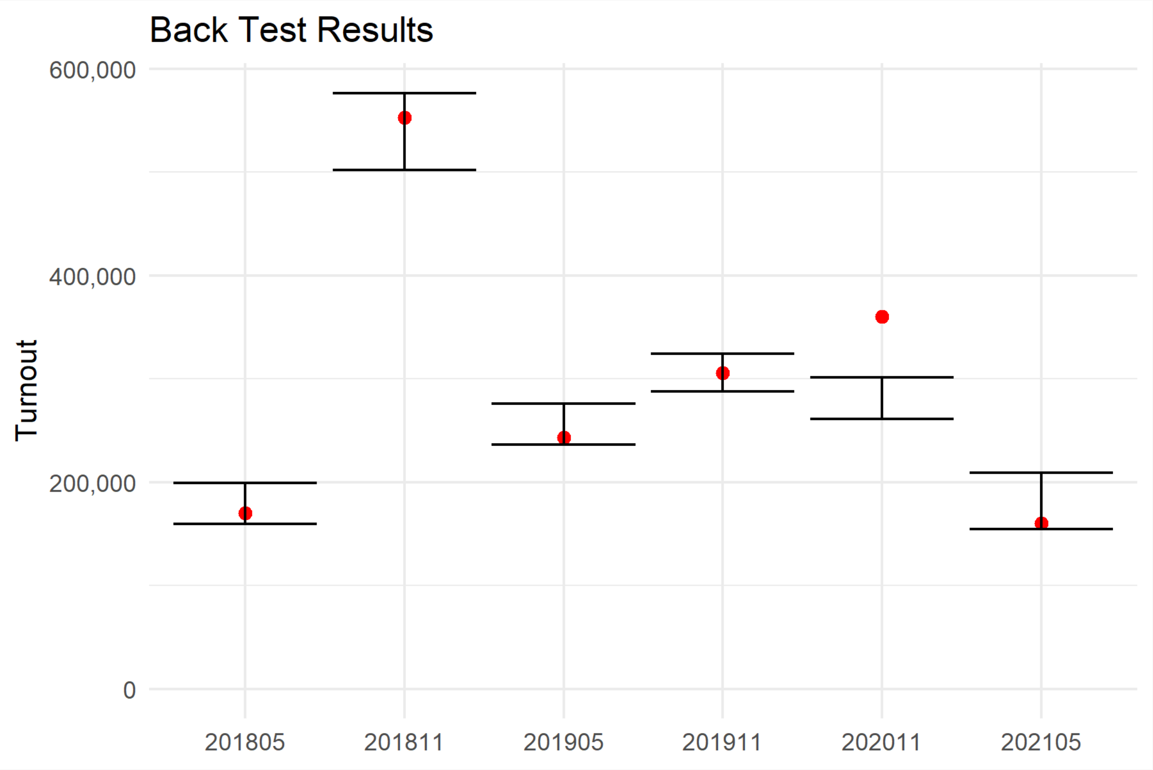
```r
library(testthat)
library(dplyr)


TRACKER_DIR <- "C:/Users/Jonathan Tannen/Dropbox/sixty_six/posts/turnout_
olddir <- setwd(TRACKER_DIR)
METHOD <- "loess"

source("R/load_data.R", chdir=TRUE)
source("R/fit_submissions.R", chdir=TRUE)
source("R/bootstrap.R", chdir=TRUE)
source("R/precalc_params.R", chdir=TRUE)

setwd(olddir)

test_elections <- tribble(
  ~folder, ~turnout,
  "phila_202105", 160e3,
  "phila_202011", 360e3,
  "phila_201911", 306e3,
  "phila_201905", 243e3,
  "phila_201811", 553e3,
  "phila_201805", 170e3
)
```



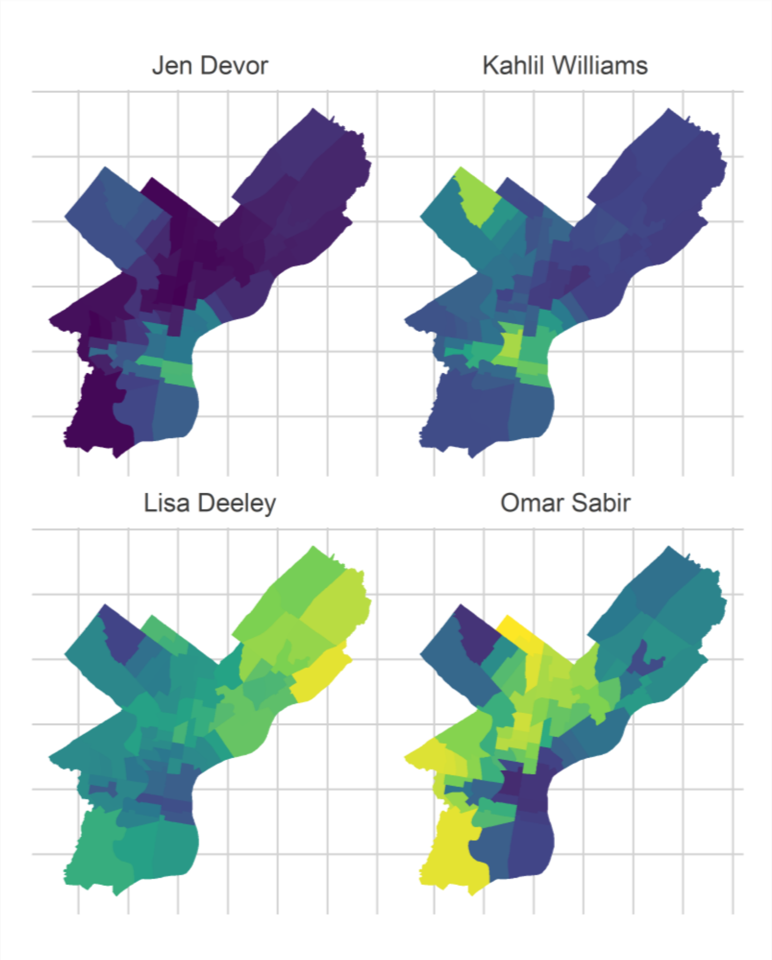
The Turnout Tracker: The Tech

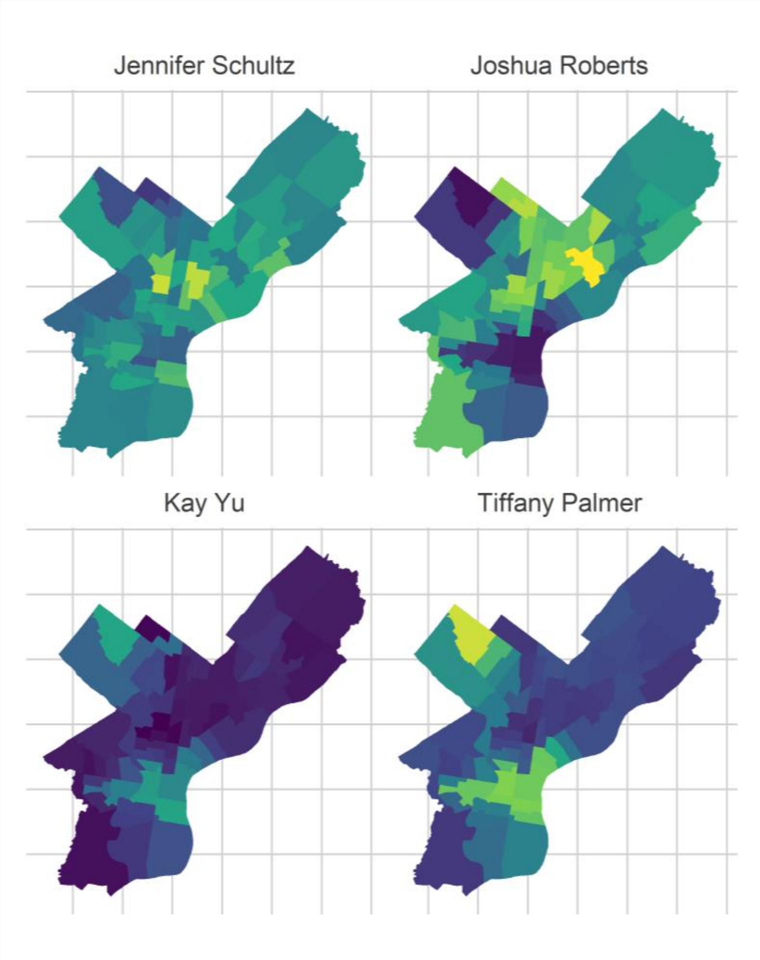
- Google Form to collect responses
- R script that downloads google sheet, processes data.
- R script that generates predictions and bootstraps.
- RMarkdown document generates HTML report.
- httr command to push html to website.

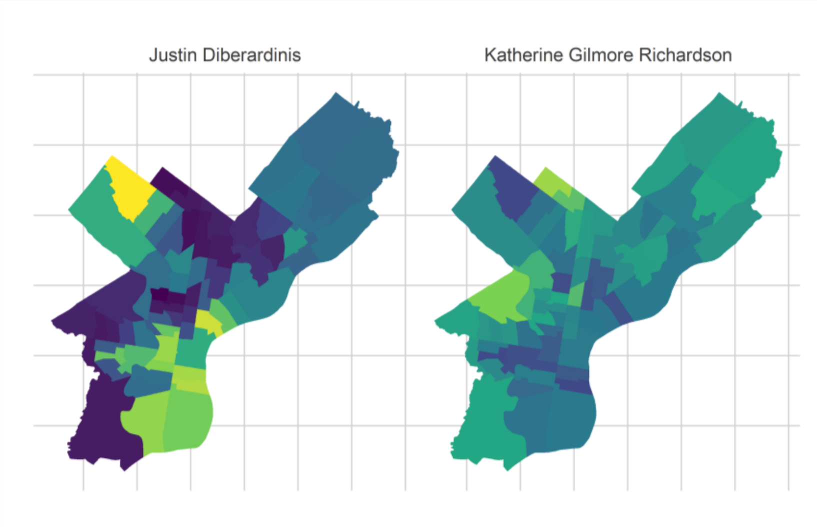
- TODO:
  - Docker Container

https://github.com/jtannen/turnout_tracker

Philadelphia's Voting Blocs

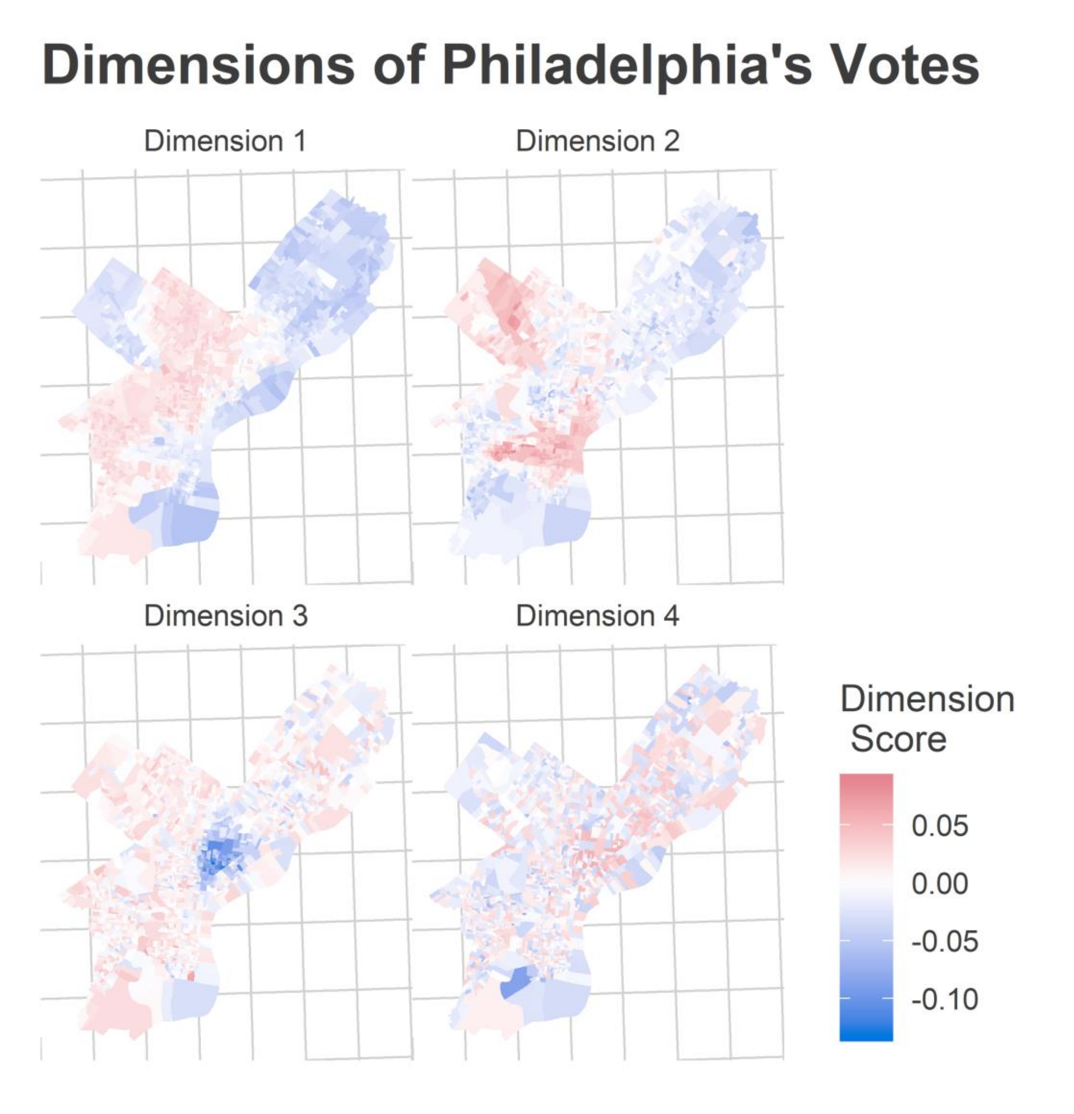






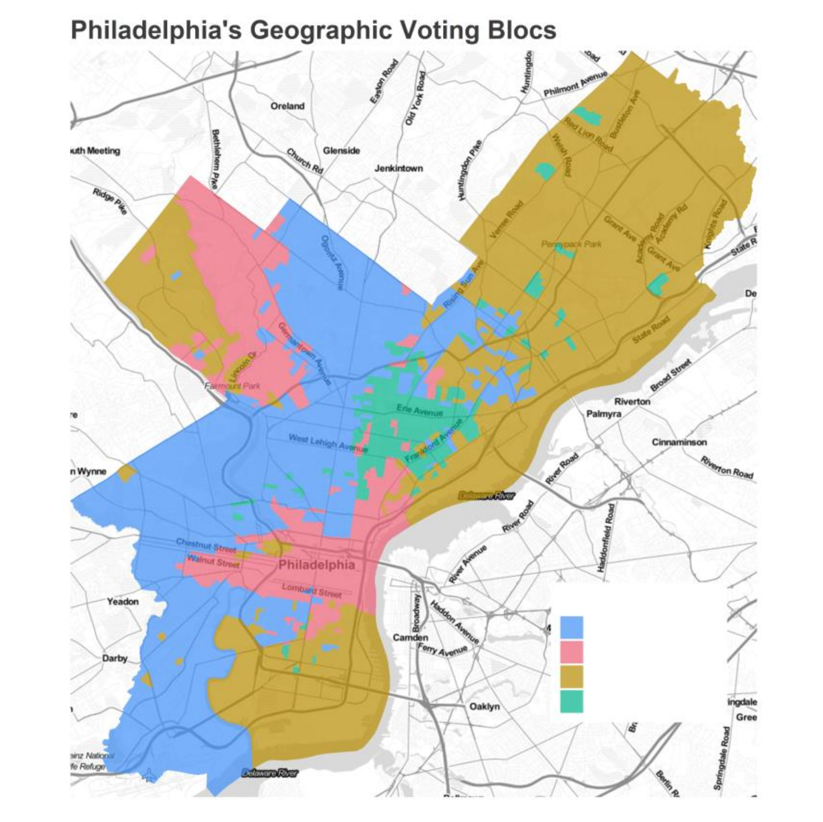
Philadelphia’s Voting Blocs

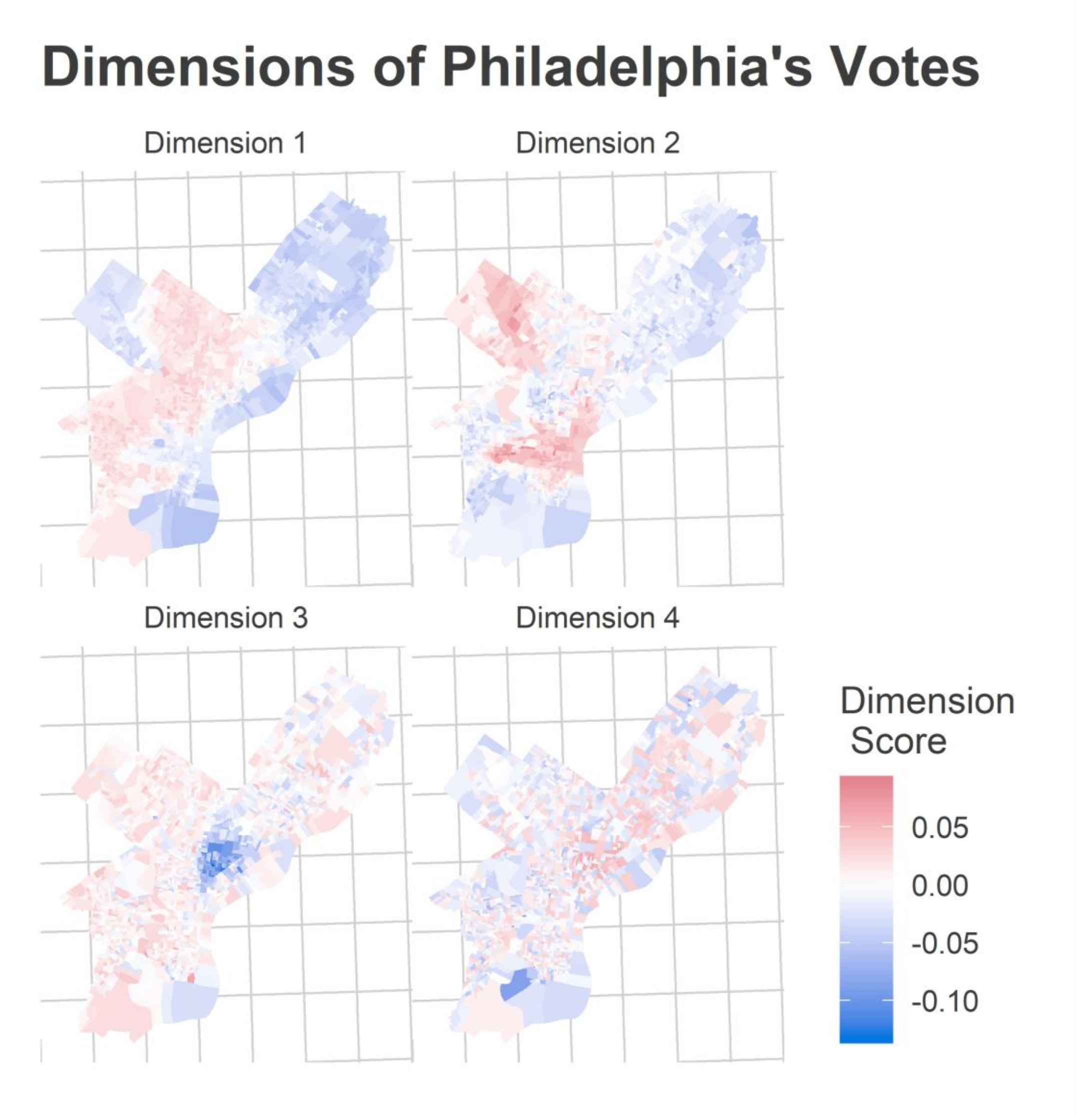
SVD to the rescue!



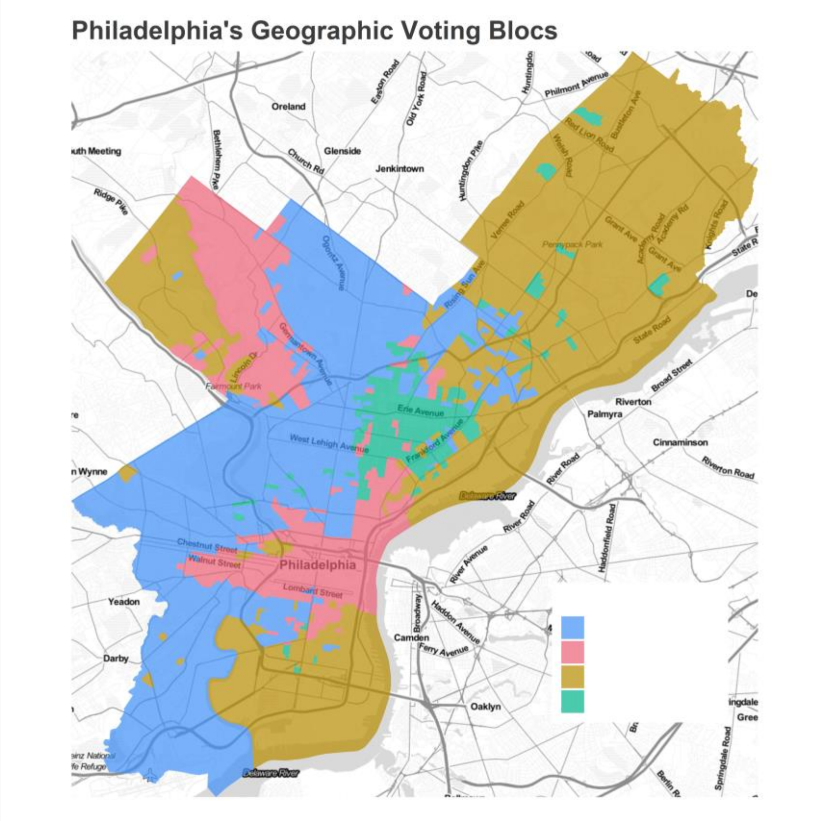
Philadelphia's Voting Blocs

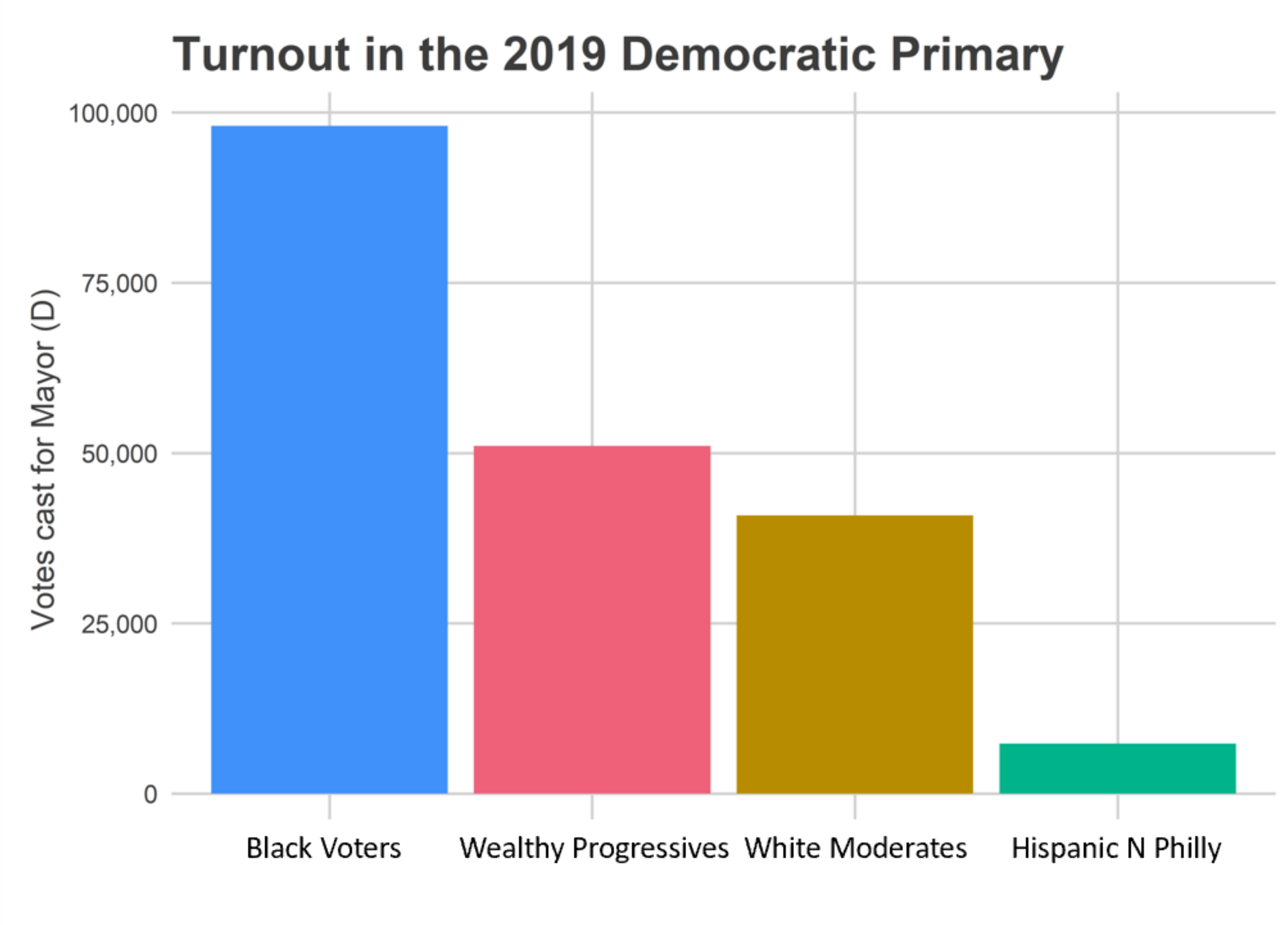
SVD + buckets to the rescue!



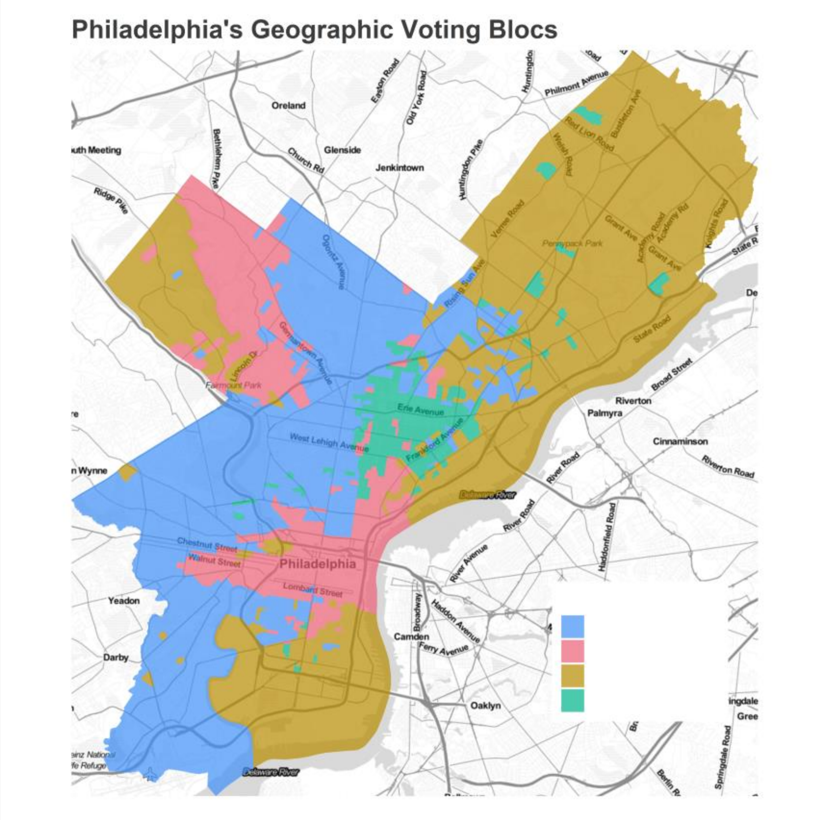


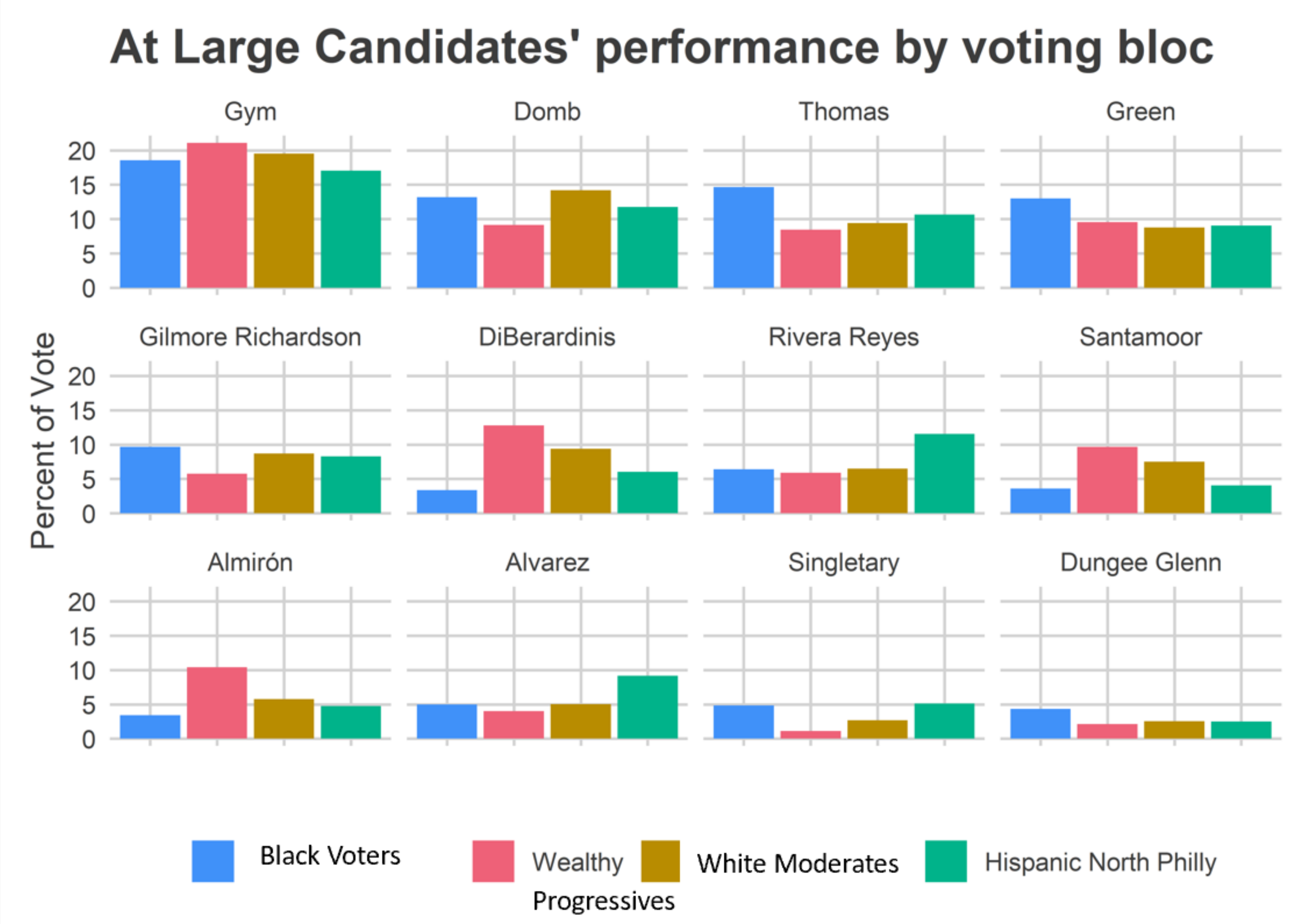
Philadelphia's Voting Blocs





Philadelphia’s Voting Blocs





The end!

Questions?

Appendix

Estimating Turnout: Time Pattern

$$\log(x_i) = \alpha_y + \mu_d + \gamma_{dy} + f(t)$$

The total city turnout at the end of the day is…

$$\sum_d \exp\{\alpha_y + \mu_d + \gamma_{dy} + f(t)\}$$

$$= \exp\{\alpha_y + f(t)\} \sum_d \exp\{\mu_d + \gamma_{dy}\}$$