FDA Rule Analysis Quarto

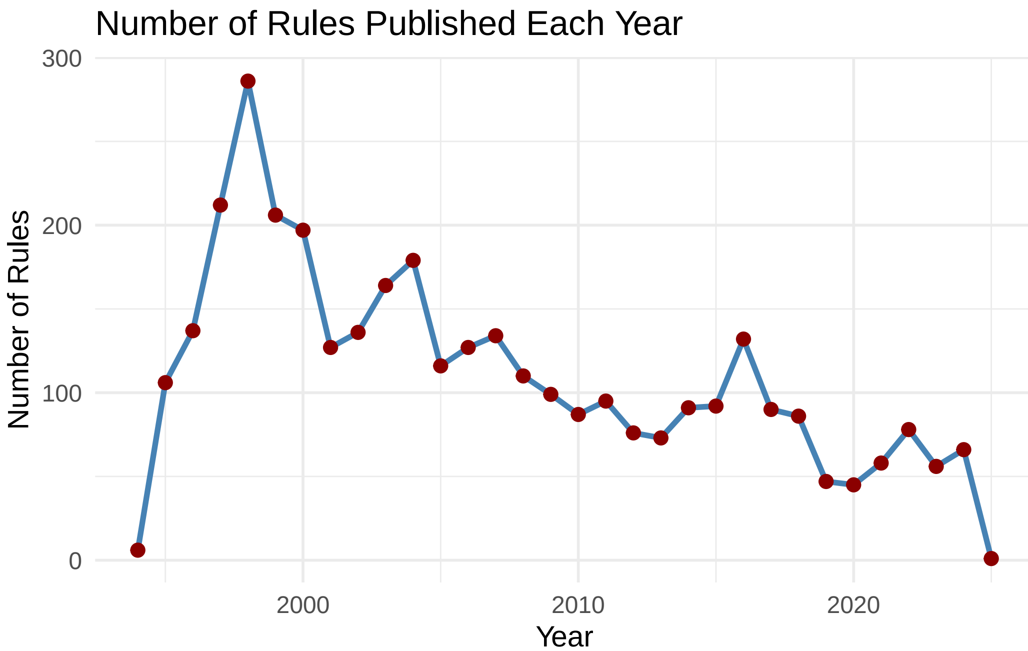
Intro

In the summer of 2024, the Supreme Court issued two landmark rulings – *Ohio v. EPA* on June 27, 2024, and *Loper Bright Enterprises v. Raimondo* on June 28, 2024 – that transformed the regulatory landscape for federal agencies. In *Ohio v. EPA*, the Court held that an agency's failure to adequately respond to significant public comments during the notice-and-comment process renders its rules arbitrary and capricious. The following day, in *Loper Bright v. Raimondo*, the Courtoverruled Chevron deference, directing lower courts to interpret statutory ambiguities independently rather than deferring to agency interpretations. In doing so, the Court substantially reduced agency latitude in interpreting legislative "gray areas".

We hypothesize that these decision created an environment where agencies are less likely to publish formal rules. The increased logistical burden of addressing public comments post-*Ohio v. EPA* and the heightened risk of litigation over statutory interpretations post-*Loper Bright* likely discourage rulemaking. To investigate this hypothesis, we employ quantitative methods—specifically, regression-discontinuity and interrupted time series analyses—using the period following the release of Loper Bright Enterprises v. Raimondo (starting June 29, 2024) as a cutoff. This study aims to empirically assess how these Supreme Court rulings have impacted agency rulemaking behavior.

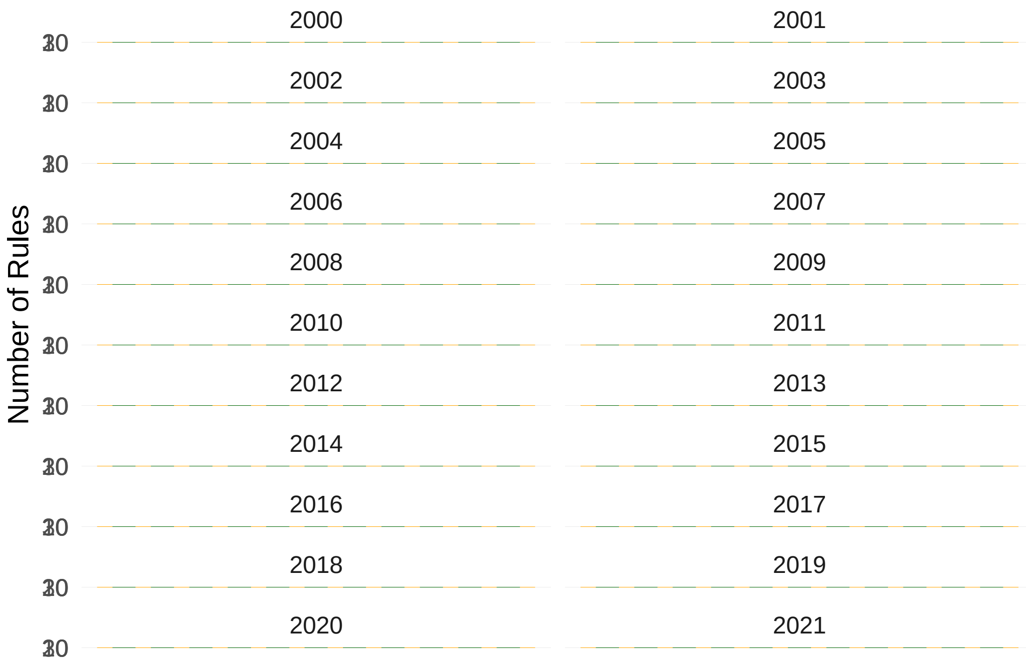
Running Code

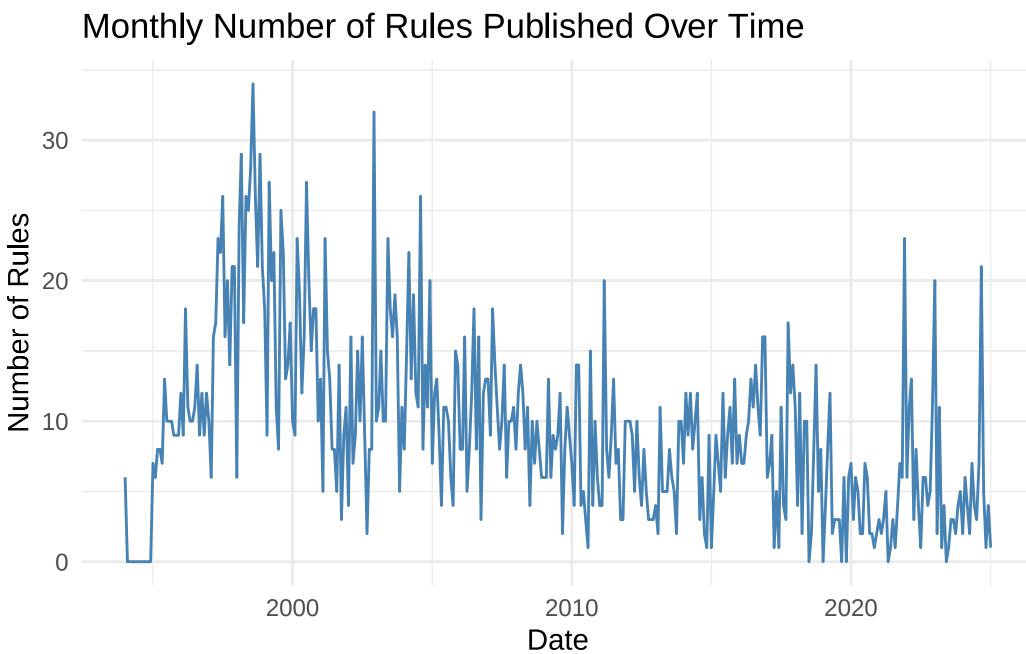
Now, create plots from df data frame



Next, let's analyze the data broken into its constituent months (the first visualization doesn't work yet)

```
`geom_line()`: Each group consists of only one observation.
i Do you need to adjust the group aesthetic?
```

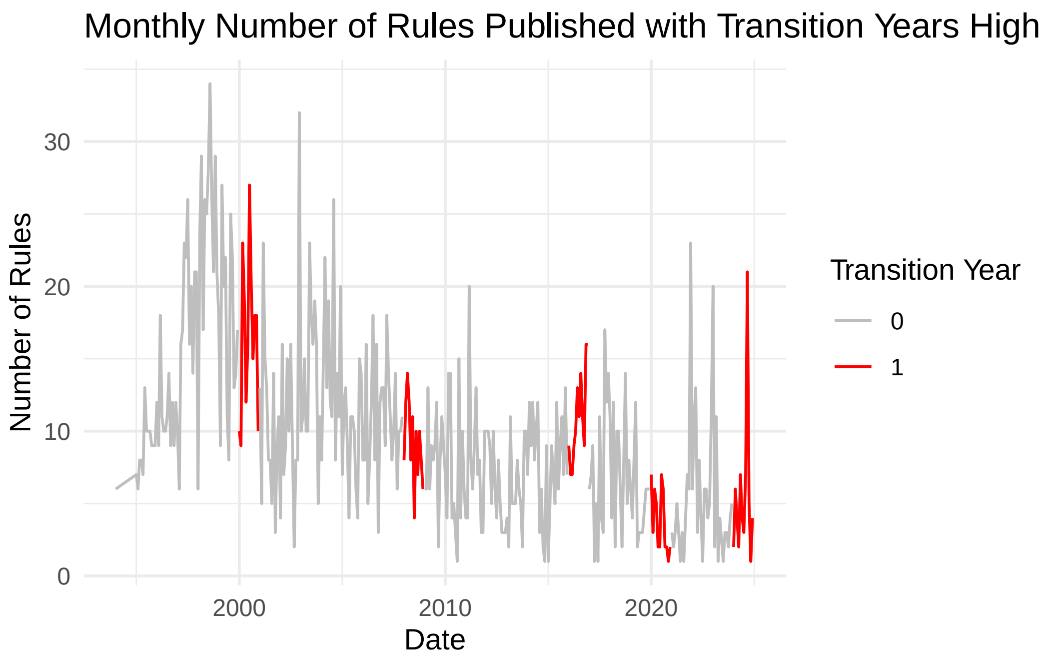




The following graph depicts the data broken into consituent months and highlights Presidential transition years.

```
`summarise()` has grouped output by 'year'. You can override using the
```

`.groups` argument.



Regression Discontinuity Analysis

$$Y_i = \alpha + \tau D_i + \beta X_i + \gamma X_i^2 + \sum_{m=1}^{11} \delta_m M_{im} + \theta T_i + \epsilon_i$$

Where:

- (Y_i): Number of Rules Published in month (i).
- (α): Intercept term (baseline level of (Y).
- (D_i): Treatment Indicator for month (i). $D_i = 1$ if month i is after June 2024 and 0 otherwise.
- (X_i): Running Variable representing the distance from the cutoff (June 2024) for month i). Measured in months: X_i = Number of months since June 2024
  - ($X_i > 0$): Post-June 2024 (treatment group)
  - ($X_i < 0$): Pre-June 2024 (control group)
- (β): The Treatment Effect

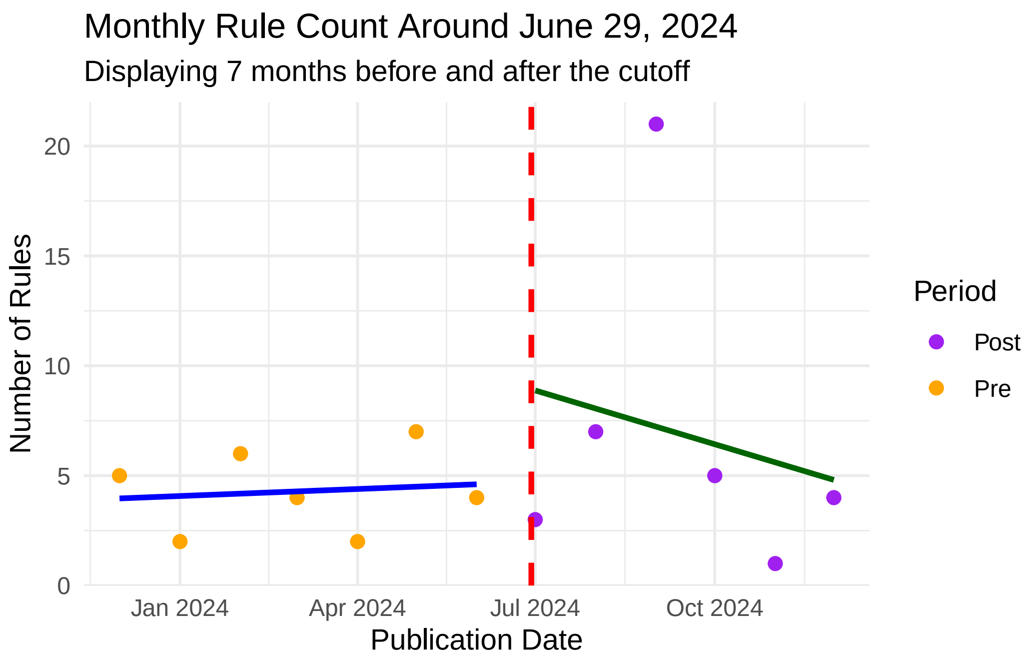
- (X_i^2): Quadratic Term to capture potential non-linear trends in the data.
- (M_{im}): Monthly Dummy Variables for each month (m, January to December), excluding one month to avoid multicollinearity (January is the reference category).
- (δ_m): Coefficients for each monthly dummy variable, capturing the effect of being in month (m) relative to the reference month.
- (T_i): Presidential Transition Indicator for month (T_i): T_i =1 for 2008, 2016, 2020, or 2024 and 0 otherwise.
- (θ): Coefficient capturing the effect associated with presidential transition years.
- (ϵ_i): Error Term capturing unobserved factors affecting (Y_i).

```
Call:
lm(formula = count ~ treatment + distance + I(distance^2) + month +
    transition, data = rules_per_month_year)

Residuals:
     Min       1Q   Median       3Q      Max
-15.9969  -3.4676  -0.7539   2.8550  21.0793

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    2.442e+00  9.451e-01   2.584  0.01016 *
treatment      3.441e+00  2.428e+00   1.417  0.15732
distance      -6.039e-02  1.139e-02  -5.303 2.01e-07 ***
I(distance^2) -9.115e-05  2.991e-05  -3.047  0.00248 **
month.L        1.017e+00  1.025e+00   0.992  0.32191
month.Q       -3.346e-01  1.022e+00  -0.328  0.74346
month.C        2.708e+00  1.025e+00   2.643  0.00859 **
month^4       -1.013e-02  1.023e+00  -0.010  0.99210
month^5        1.645e+00  1.024e+00   1.606  0.10905
month^6        1.175e+00  1.025e+00   1.147  0.25231
month^7       -2.539e+00  1.025e+00  -2.477  0.01372 *
month^8        1.699e+00  1.025e+00   1.658  0.09827 .
month^9       -1.833e+00  1.025e+00  -1.788  0.07466 .
month^10       9.035e-01  1.025e+00   0.881  0.37868
month^11      -3.537e-01  1.025e+00  -0.345  0.73034
transition     4.935e-01  9.685e-01   0.510  0.61070
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 5.707 on 357 degrees of freedom
Multiple R-squared:  0.2594,    Adjusted R-squared:  0.2283
F-statistic: 8.338 on 15 and 357 DF,  p-value: 2.379e-16
```

Now, let's visualize the RD regression, displaying the number of rules published in the 7 months before and after the cutoff date

```
`geom_smooth()` using formula = 'y ~ x'
`geom_smooth()` using formula = 'y ~ x'
```



Now we'll try an ITS model.

```
Warning: package 'forecast' was built under R version 4.3.3
```

```
Registered S3 method overwritten by 'quantmod':
  method            from
  as.zoo.data.frame zoo
```

```
     Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
1994   6   0   0   0   0   0   0   0   0   0   0   0
1995   7   6   8   8   7  13  10  10  10   9   9   9
```

1996	12	9	18	11	10	10	11	14	9	12	9	12
1997	10	6	16	17	23	22	26	16	20	14	21	21
1998	6	24	29	17	26	25	28	34	26	21	29	21
1999	18	9	27	20	22	11	8	25	22	13	14	17
2000	10	9	23	19	12	16	27	20	15	18	18	10
2001	13	5	23	15	13	8	8	5	14	3	9	11
2002	4	16	7	9	15	10	16	9	2	8	8	32
2003	10	11	15	10	10	23	18	16	19	16	5	11
2004	8	15	22	13	19	12	11	26	8	14	11	20
2005	7	12	13	9	4	11	11	10	6	4	15	14
2006	8	8	16	5	8	12	18	8	16	3	12	13
2007	13	9	18	14	11	8	10	14	6	10	10	11
2008	8	12	14	12	8	11	4	10	7	10	8	6
2009	6	6	13	6	9	8	9	12	2	8	11	9
2010	7	4	14	14	4	5	3	1	15	4	10	6
2011	4	4	20	8	6	9	13	7	8	3	3	10
2012	10	10	9	5	10	6	4	8	5	3	3	3
2013	4	2	11	5	5	5	8	6	5	2	10	10
2014	7	12	9	12	8	10	12	3	6	2	1	9
2015	1	5	9	7	5	12	6	9	11	7	13	7
2016	9	7	7	9	10	13	11	14	11	9	16	16
2017	6	7	9	1	5	1	11	4	3	17	12	14
2018	11	4	12	2	10	10	0	2	8	14	5	8
2019	0	4	8	12	2	3	3	3	0	6	0	6
2020	7	3	6	5	2	2	7	6	2	2	1	2
2021	3	2	3	5	0	1	3	1	4	7	6	23
2022	6	11	13	3	8	4	1	6	6	4	5	11
2023	20	2	11	1	4	0	1	3	3	2	4	5
2024	2	6	4	2	7	4	3	7	21	5	1	4
2025	1											

```
Series: ts_rules
Regression with ARIMA(1,1,1)(0,0,2)[12] errors

Coefficients:
          ar1      ma1    sma1    sma2  Intervention  TimeAfterIntervention
      -0.0252  -0.7832  0.0634  0.1128        7.2282                -1.3801
s.e.   0.0677   0.0442  0.0522  0.0519        4.3234                 0.9158

sigma^2 = 23.73:  log likelihood = -1114.51
AIC=2243.02   AICc=2243.32   BIC=2270.45
```

```
Training set error measures:
                      ME     RMSE      MAE  MPE MAPE      MASE         ACF1
Training set 0.003090028 4.825542 3.629745 -Inf  Inf 0.6842496 0.0004223061
```