The Trade War Effect on Donald Trump's Approval Rate

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5/13/2022

Introduction

This paper's purpose is to use RD to determine the impact of Trade War on Donald Trump's approval rate during his presidency.

Background

The trade war is arguably one of the most impactful actions that Donald Trump has made in his term of office. In 2018 he started a trade war with the world involving multiple battles with China as well as other American trade partners (EU, Canada, Mexico, etc.). Trump imposed tariffs and/or quotas on imports from the trade partners of the U.S. using a particular US legal rationale, such as "global safeguard" restrictions. Subsequent retaliation by trading partners and the further escalation between China and America has affected a list of items across industries, significantly risked trades, investment as well as the global economy (Chad P. Bown and Melina 2022). The reason of trade war remains under debate, some experts view this trade war as another form of the global struggle between China, other scholars maintain that Trump wants to re-industrialize the US. The trade war is also analyzed from financial perspective, creating new arguments (Di, Luft, and Zhong 2019). In Joseph R. Biden Jr.'s presidency the tariffs on steel and aluminum was lifted or eased but some imposed tariffs remain.

Multiple paperwork provided evidence that the adverse economic effects of trade wars. Simulation of this possible China-US trade war estimated that the trade war would hurt manufacturing employment, and both export and import in the US, but would gain on welfare, GDP, and non-manufacturing production (C. Li, He, and Lin 2018) . After Trump's announcement the first tariff and the following retaliations from targeted countries, economists estimated a welfare cost of around \$6.9 billion during only the first 11 months of 2018, the U.S. tariffs were almost passed through into U.S. domestic prices, trade war created an additional cost of \$12.3 billion to the consumers (Amiti, Weinstein, and Redding 2019). Among the most significant trade events in the recent history, the overall welfare impacts of trade war were modest, ranged from -0.2% to -0.4% for the United States, sectoral revenue and the pattern of international trade are largely affected(M. Li, Balistreri, and Zhang 2020).

Retaliations from the US's trade partners have political impacts as well, they have not only disproportionately targeted more Republican areas, but they were also carefully targeted to hurt Trump. A relevant industry's concentration in Republican-leaning districts is systematically associated with higher probability of being targeted in early rounds of retaliation. Strong evidence shows that for every percentage point increase in the share of workers exposed to China's retaliatory tariffs, the Republican share of the vote decreased by 0.12 to 0.47 percentage points compared to the previous election, depending on the time of exposure (Kim and Margalit 2021). A similar negative association was found between local exposure of the economic consequences of the trade war and the decline in support and a loss of seats for Republican candidates in the 2018 House elections(Chad P. Bown, Chor, and Blanchard 2019). Empirical evidence from individual-level data and county-level data shows that counties that are more exposed to retaliatory tariff had higher levels of support for Trump in the 2016 presidential election: the counties most exposed to EU retaliation saw an average swing in the Republican candidates' vote share of 22% verses counties not exposed to EU retaliation (Fetzer and Schwarz 2021). Individuals living in the counties under the highest EU retaliation exposure would be characterized by a 31.5% higher propensity to express a favorable view of Trump as a candidate, and for China's retaliation, the propensity is 11.6% (Fetzer and Schwarz 2021). Targeting of Republican counties in swing districts appears to be concentrated in the first two rounds of retaliation. While a ten-percentage-point increase in the two-party vote share of the Republican party is associated with a 0.12 percentage point increase in the share of the targeted workforce in non-swing districts, the targeted share of the workforce is higher by 0.5 points in swing districts (Kim and Margalit 2021). The retaliatory tariffs appear to have a clear political purpose: damage Donald Trump's support rates in the red states and swing states.

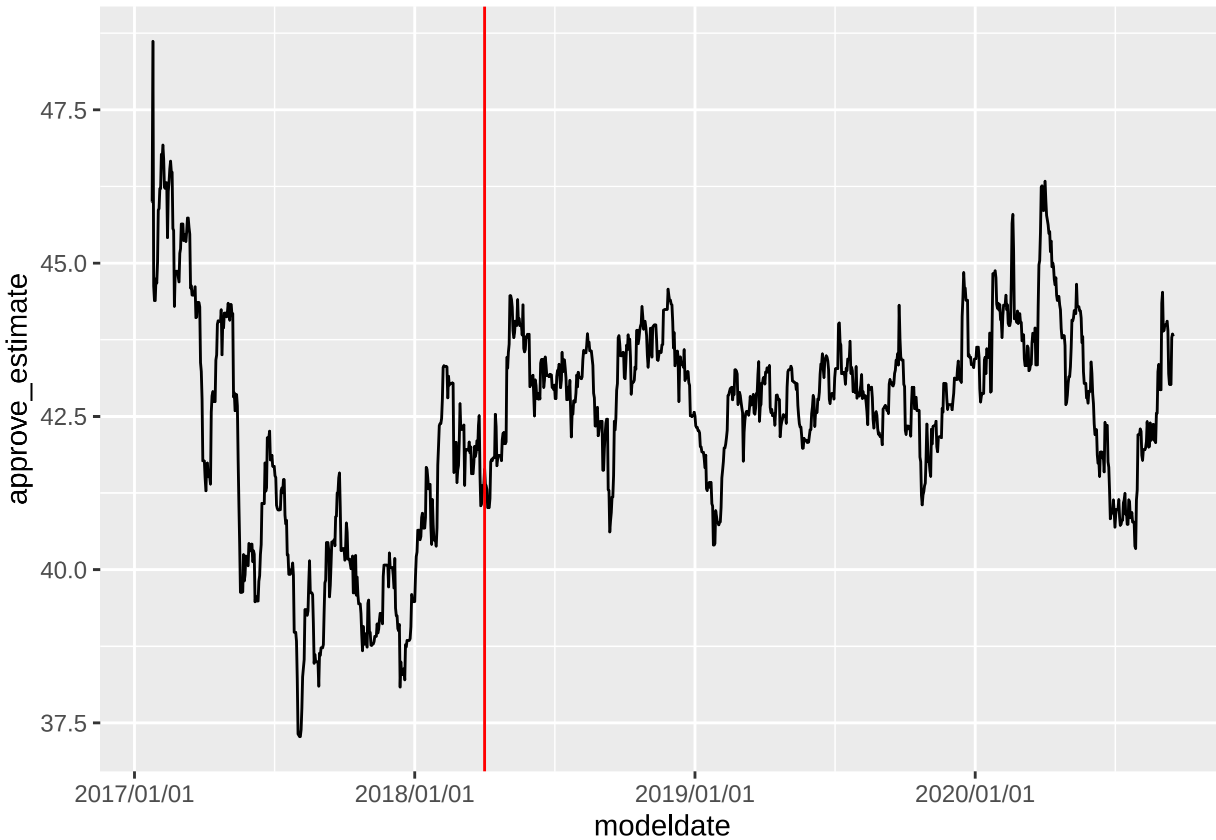
Data

To examine trade war and its electoral consequences, we developed a regression discontinuity in time model. Combining with approval ratings of Donald Trump during his term of office, we measure the percentage change of Donald Trump's estimated job approval rates from registered or likely voter polls.

Historically, the president's approval ratings have been one of the best indicators of how his party will fare in congressional elections (Silver 2017). Therefore, we use a dataset that was made by FiveThirtyEight, and published to Kaggle (Mukherjee 2020; Silver 2017). It contains a daily trendline of Donald Trump's low, high, and estimated job approval ratings across January 23rd, 2017, to September 15th, 2020, as well as his low, high, and estimated job disapproval rating across the same period. All the polls collected are considered real, scientific surveys, they are weighed based on their methodological standards, historical accuracy, sample size and how often a pollster measures Trump's approval ratings, as well as a series of rigorous adjustments. The approval ratings polls included only registered or likely voter polls. For this study, we use Donald Trump's estimated approval rate from January 23rd, 2017 to September 15th, 2020 as the key value.

Table 1: Approval rate

	N	Mean	Sd
high approval	62382.19	46.83	1.75
low approval	50710.58	38.07	1.72
estimated approval	56546.38	42.45	1.69
high disapproval	76141.12	57.16	1.89
low disapproval	65114.70	48.88	2.07
estimated disapproval	70627.91	53.02	1.93



Research Design

While evaluating a question of how a policy would change the approval rate of one party, there is no cross-sectional variation in treatment-only one party is observed at a given time, so no difference-in-differences is possible. However, it is possible to estimate the impact under a regression discontinuity (RD) context. In this study, we used regression discontinuity in time (RDiT) to measure the trade war's average effect on Donald Trump's approval rate. Different from cross-sectional RD, the running variable is time itself in the RDiT framework, and time cannot be thought of as randomly assigned within a neighborhood around a threshold like RD framework assigning randomized experiment (Hausman and Rapson 2018). In our model, the date of retaliatory tariffs went into effect c is the cutoff point. For all dates $t>c$, Trump's job approval rate is affected, and for all dates $t<c$, it is not. China imposed its first retaliatory tariff on US products in April, 2, 2018 and in July, 6, 2018, the first part of its updated retaliation list targeting roughly $34 billion out of $50 billion of US exports, including a lot of agricultural and food products went into effect (Chad P. Bown

and Melina 2022). These two tariffs have heavy impact on the US trade and domestic consumers. Since we know the date of tariff going into effect precisely well, by assuming that the treatment effect is smooth and constant throughout the postperiod, which means the rate of tariffs are constant and they do not jump or fall across time, this allows the RDiT to perform well.

During Trump's presidency, other potential confounders have effects on his approval rate as well, they are correlated with the running variable and may have discontinuous impacts on the potential outcome. We specify control variables such as major tariffs imposed between US and its trade partners from 2018 to 2020, as well as Donald Trump's subsidies for American farmers after export fallout in July 24, 2018. In March 13, 2020, the first case of COVID-19 in US was announced, we include this event as control as well. These controls are dummy variables that equal to 0 before and equal to 1 in and after their dates. We assume that the controls observed all other potential confounders, and these confounders change smoothly across the date of their implementations.

Table 2: Control Variables

Events	Date
Trump announced tariffs on trading partners	March 1, 2018
Announced tariff went into effect	March 23, 2018
US lifts tariffs on Canada and Mexico	May 17, 2018
EU retaliates	June 22, 2018
Canada retaliates	July 1, 2018
Farmer subsidies implemented	July 24, 2018
Chinese second phase of tariffs on US goes into effect	September 24, 2018
Trump broadened tariffs	January 24, 2020
First case of COVID-19 in US	March 13, 2020

There are some assumptions that our model holds other than smooth and constant treatment effect and controls observing all other confounders. The first key assumption is that absent the trade war itself, the expected potential outcomes would have remained a smooth function even passing the cutoff points. Therefore, if continuity holds, only the trade war, triggered at April , 2, 2018 and June, 15, 2018 could be responsible for discrete change in Donald Trump's job approval rate. Our data passed the continuity assumption test, nothing else is changing at the given dates that would otherwise shift potential outcomes (Cunningham 2021). We also assume that there is no lag effect of trade war, once the tariffs went into effect, the impact was instantly perceived and changed corresponding approval rate of Donald Trump.

The process of RDiT is given by the following equation:

$$y_{i,t} = \alpha + \beta_1\{t \geq t_{start}\} + \beta_2\{t \geq t_{start}\}^2 + \cdots + \beta_p\{t \geq t_{start}\}^p + B_0C_0 + B_1C_1 + \cdots B_9C_9 + \eta_{i,t}$$

Where:

$$\beta = lim_{t \to t_{start}} E[y_i \mid t = t_{start}] - lim_{t \leftarrow t_{start}} E[y_i \mid t = t_{start}]$$

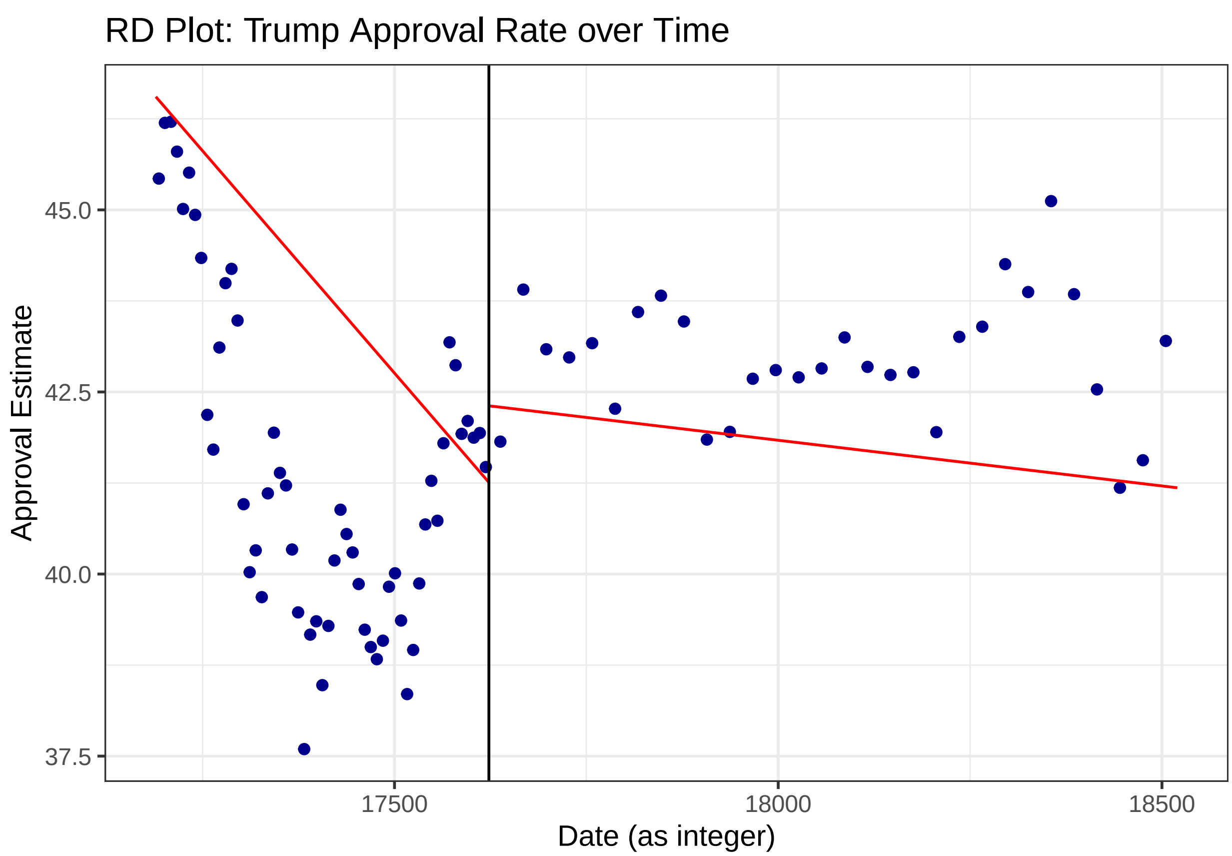
The first variable, $a = \beta_0 - \beta_p\{t \geq t_{start}\}^p$ shifts the intercept up and down. β_p whcih captures the effect of trade war, has the same interpretation, except for the intercept. It comes with p^{th} order polynomial. In this study we present models with linear and second order polynomial. C_{0-9} represents the control variables, B_{0-9} are their coefficients. And $\eta_{i,t}$ is the error term.

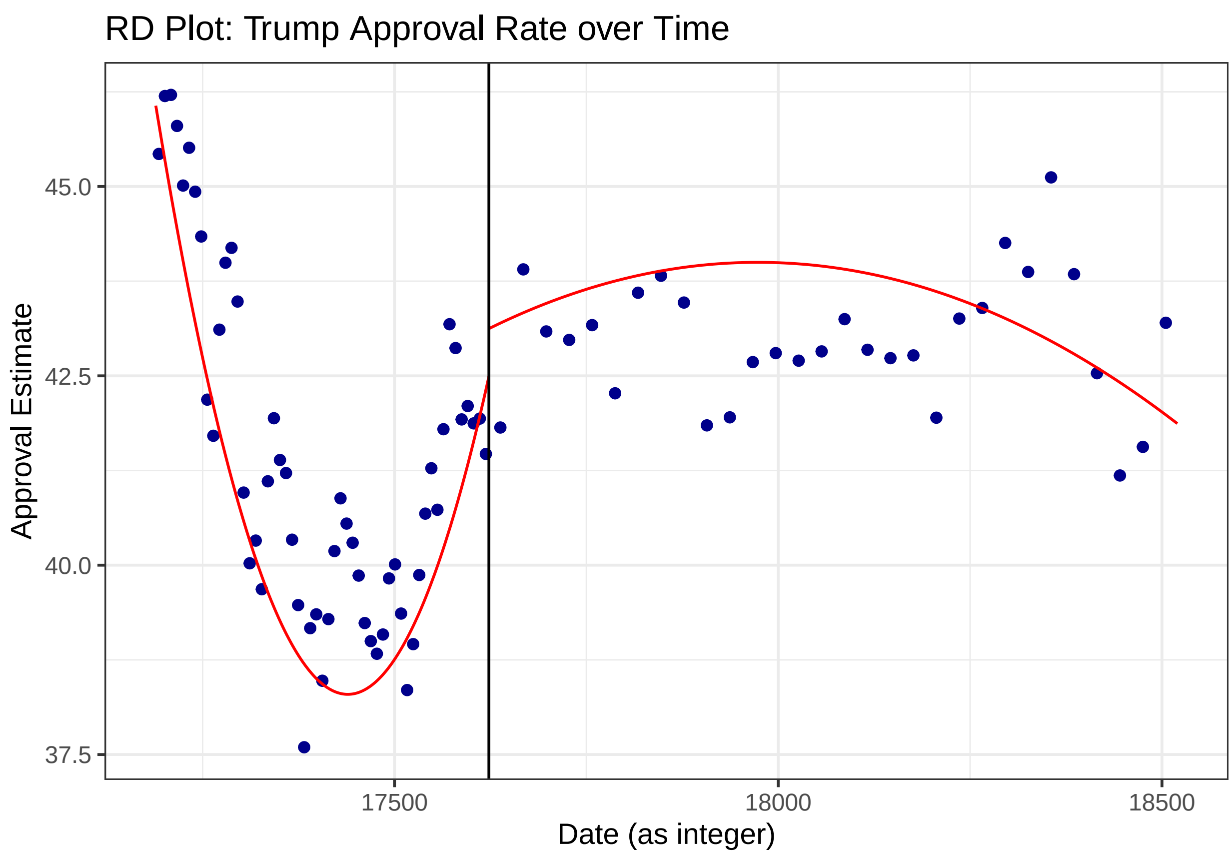
Table 3: RD Estimates for Approval Rate after U.S. Tariffs

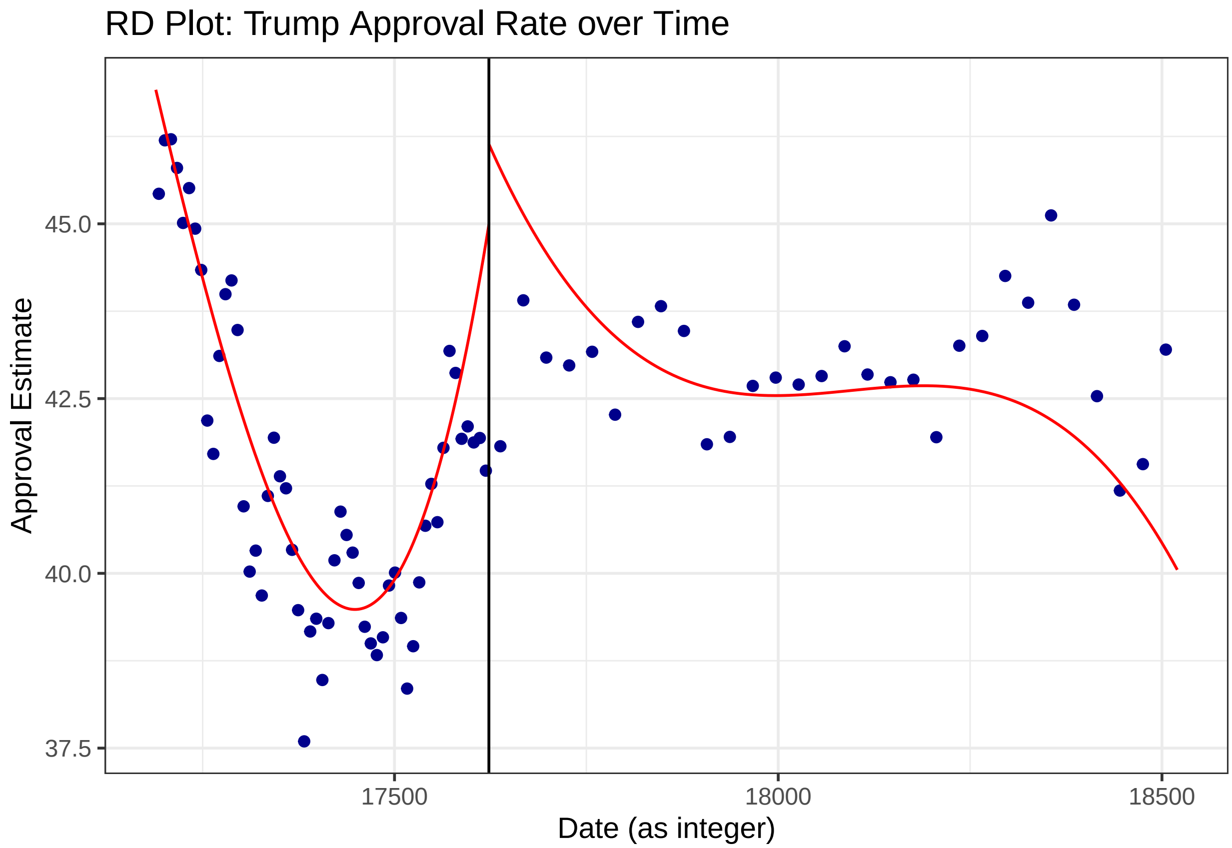
	Model 1	Model 2	Model 3	Model 4
Conventional	−0.369**	−0.200	−0.518***	−0.319*
	(0.118)	(0.150)	(0.130)	(0.133)
Bias-Corrected	−0.415***	−0.314*	−0.519***	−0.299*
	(0.118)	(0.150)	(0.130)	(0.133)
Robust	−0.415**	−0.314	−0.519***	−0.299*
	(0.136)	(0.285)	(0.145)	(0.141)
Kernel	Triangular	Triangular	Triangular	Triangular
Bandwidth	mserd	mserd	mserd	mserd

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Discussion of Results




RD Plot: Trump Approval Rate over Time
Approval Estimate
45.0
42.5
40.0
37.5
17500
18000
18500
Date (as integer)

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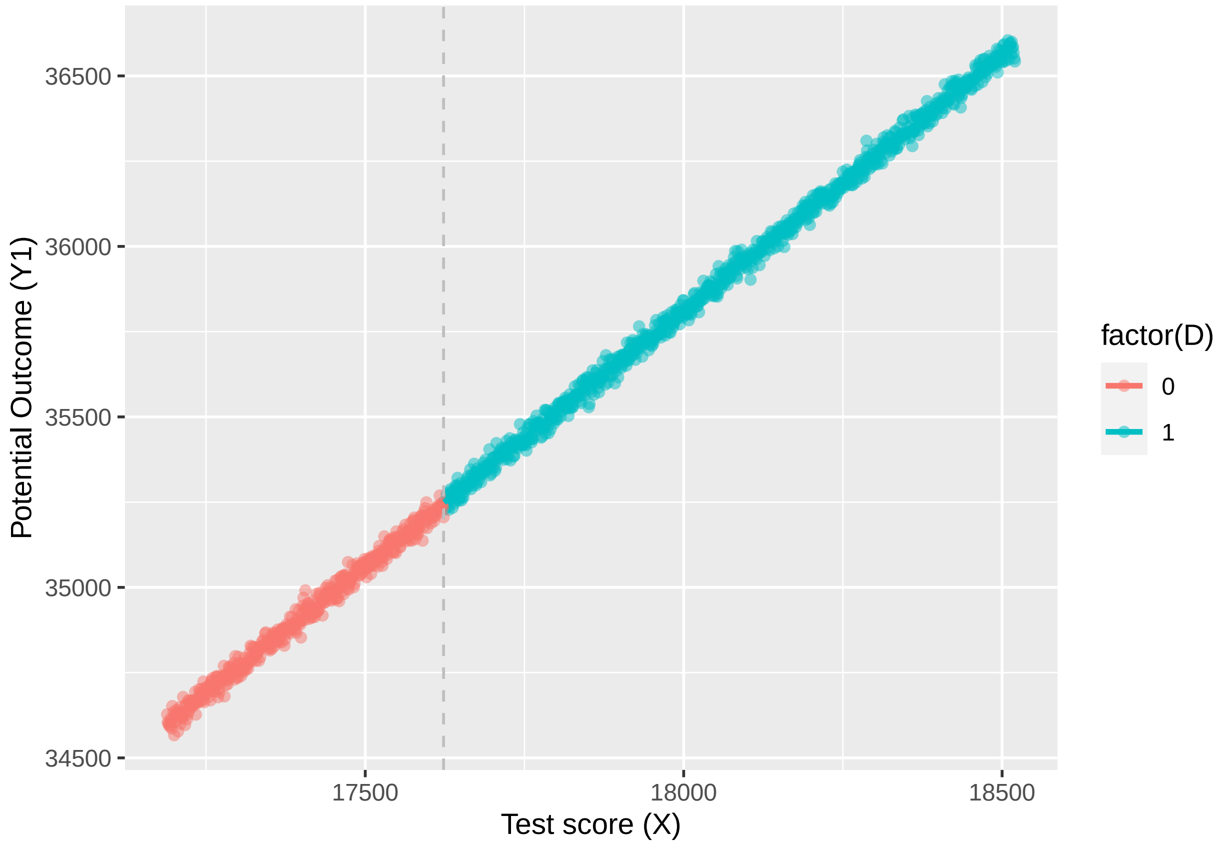
## `geom_smooth()` using formula 'y ~ x'
```

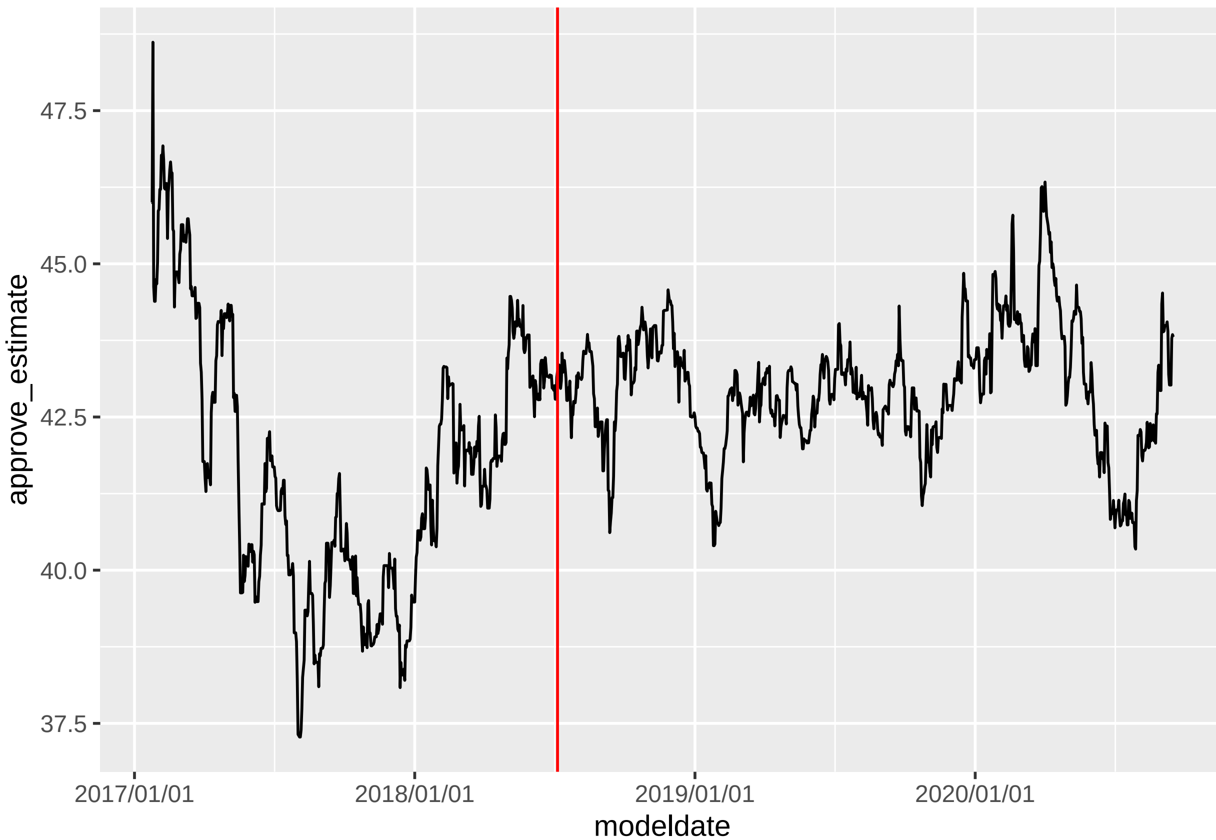


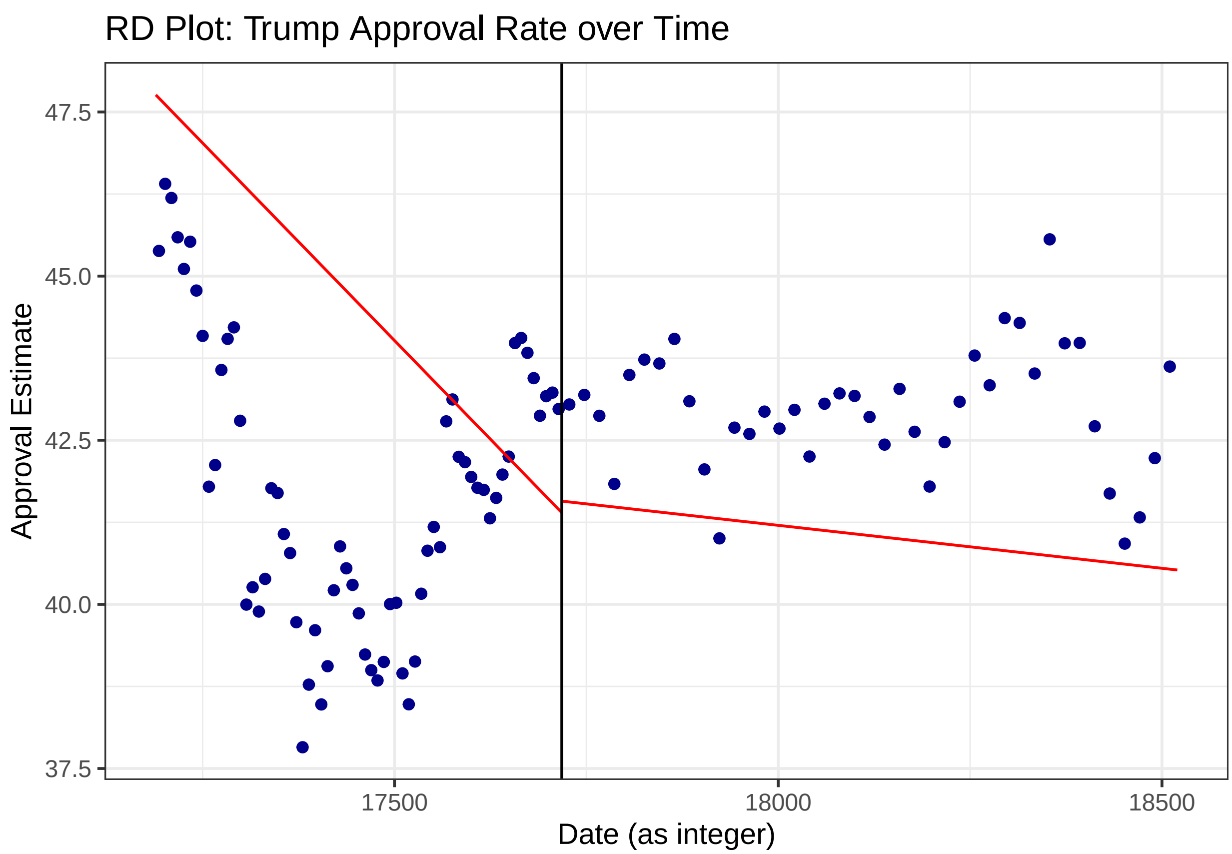
Potential Outcome (Y1)
36500
36000
35500
35000
34500
17500
18000
18500
Test score (X)
factor(D)
0
1

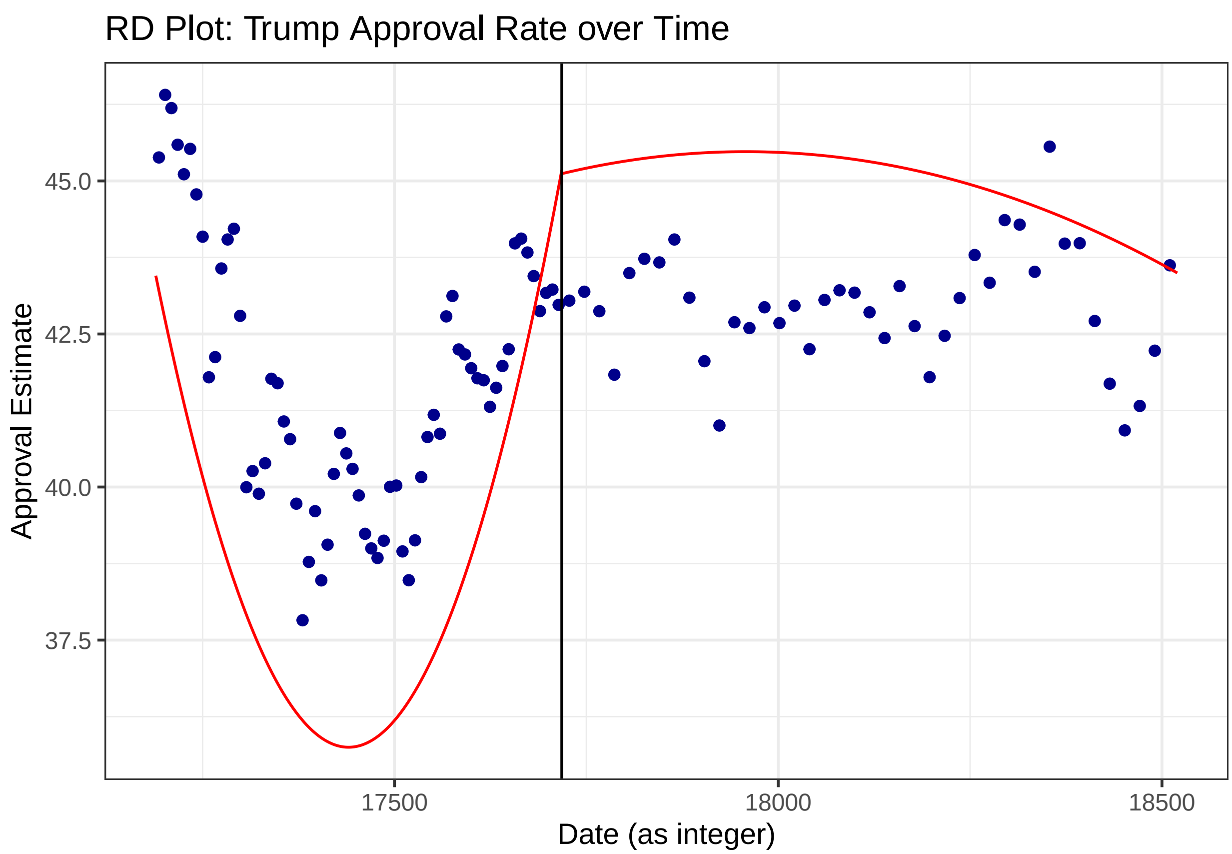
Table 4: RD Estimates for Approval Rate after China Tariffs

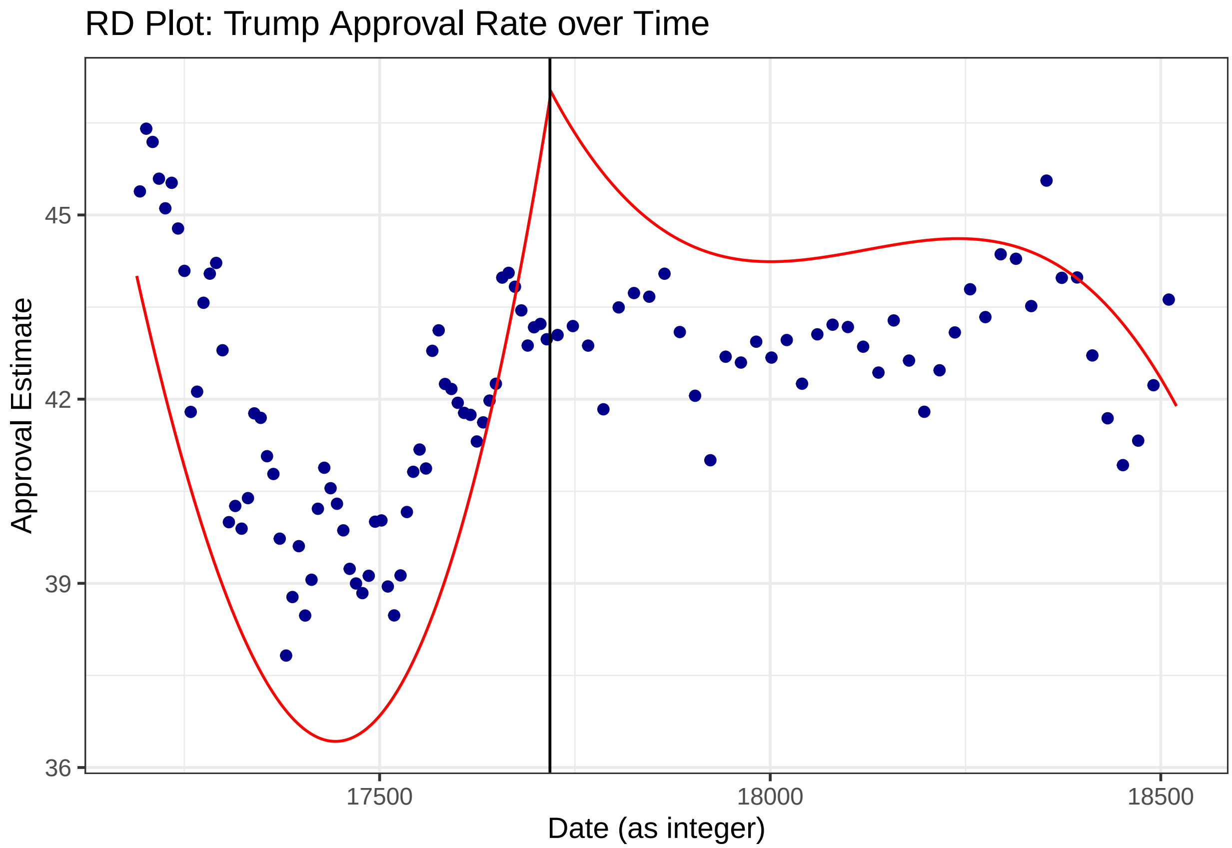
	Model 1	Model 2	Model 3	Model 4
Conventional	0.185*	0.192**	0.106	0.543***
	(0.077)	(0.063)	(0.080)	(0.124)
Bias-Corrected	0.161*	0.476***	0.146+	0.480***
	(0.077)	(0.063)	(0.080)	(0.124)
Robust	0.161+	0.476***	0.146+	0.480***
	(0.095)	(0.074)	(0.086)	(0.127)
Kernel	Triangular	Triangular	Triangular	Triangular
Bandwidth	mserd	mserd	mserd	mserd

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$




RD Plot: Trump Approval Rate over Time
47.5
45.0
42.5
40.0
37.5
Approval Estimate
17500
18000
18500
Date (as integer)


RD Plot: Trump Approval Rate over Time
Approval Estimate
45.0
42.5
40.0
37.5
17500
18000
18500
Date (as integer)

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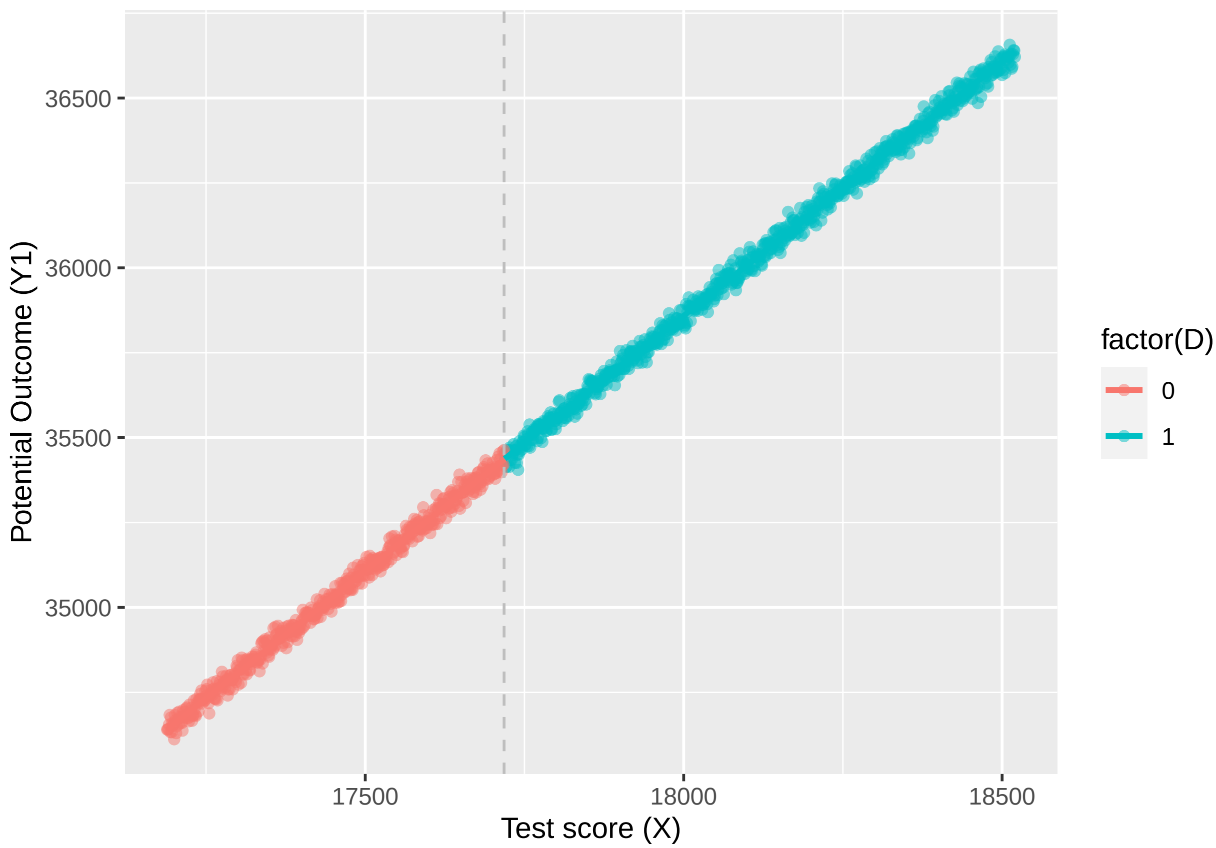
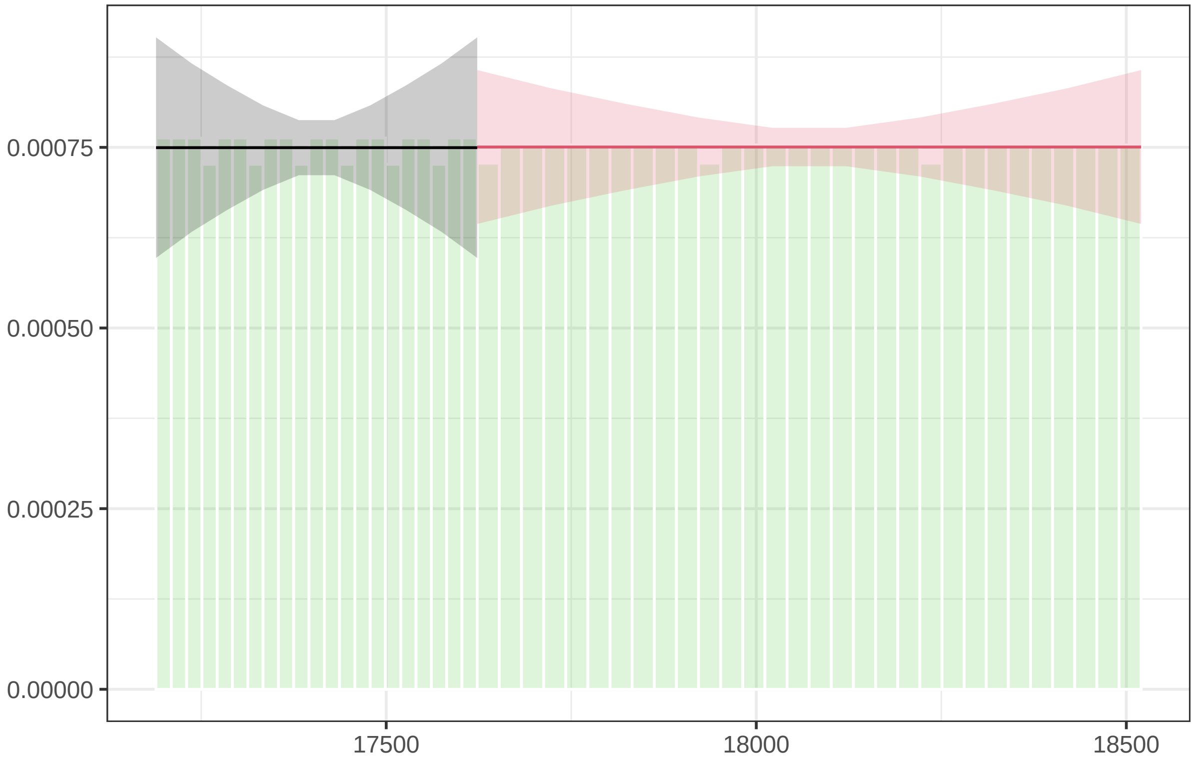
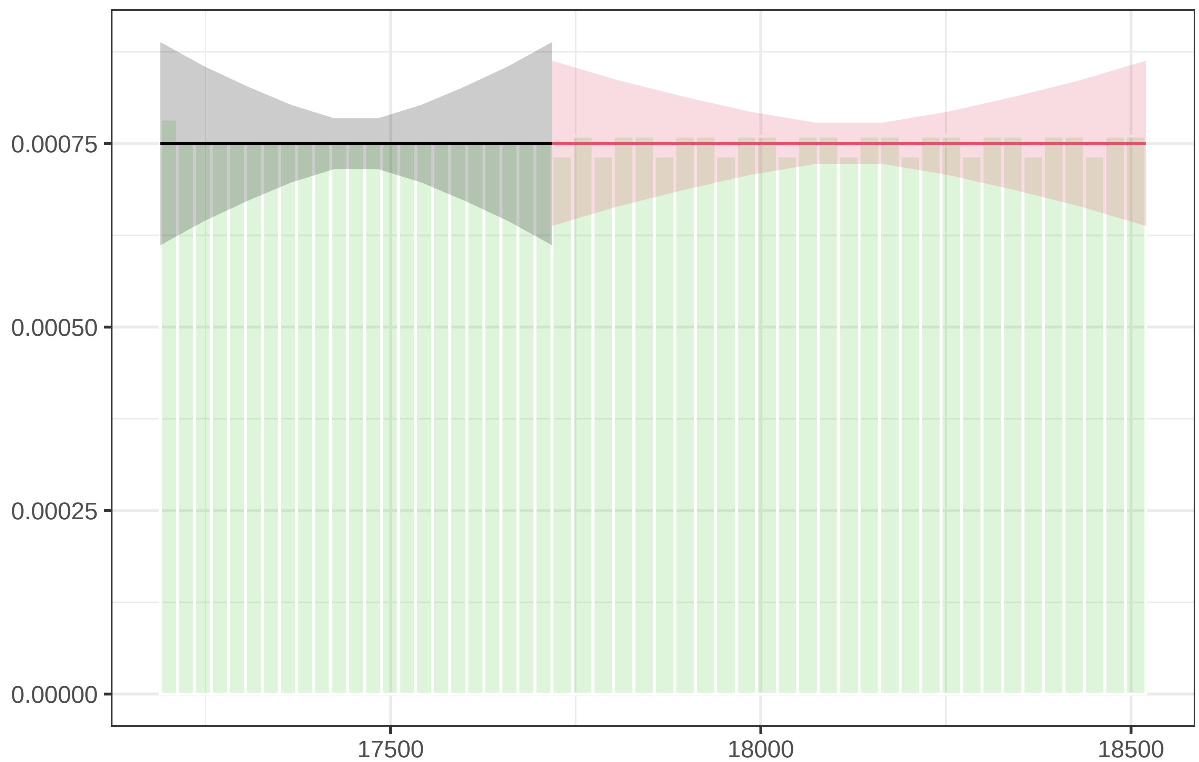

Potential Outcome (Y1)
36500
36000
35500
35000
17500
18000
18500
Test score (X)
factor(D)
0
1


0.00075
0.00050
0.00025
0.00000
17500
18000
18500



Conclusion

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