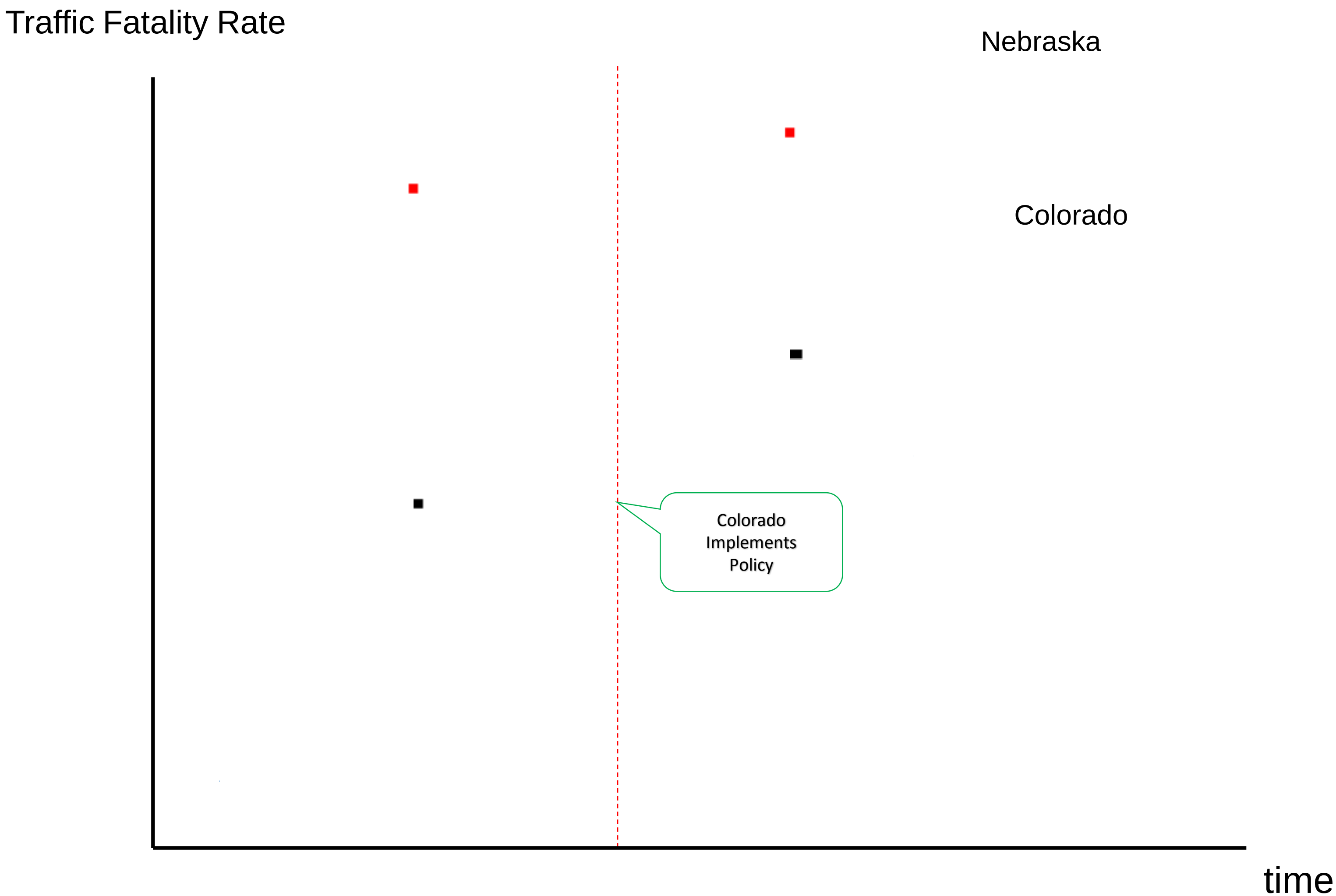
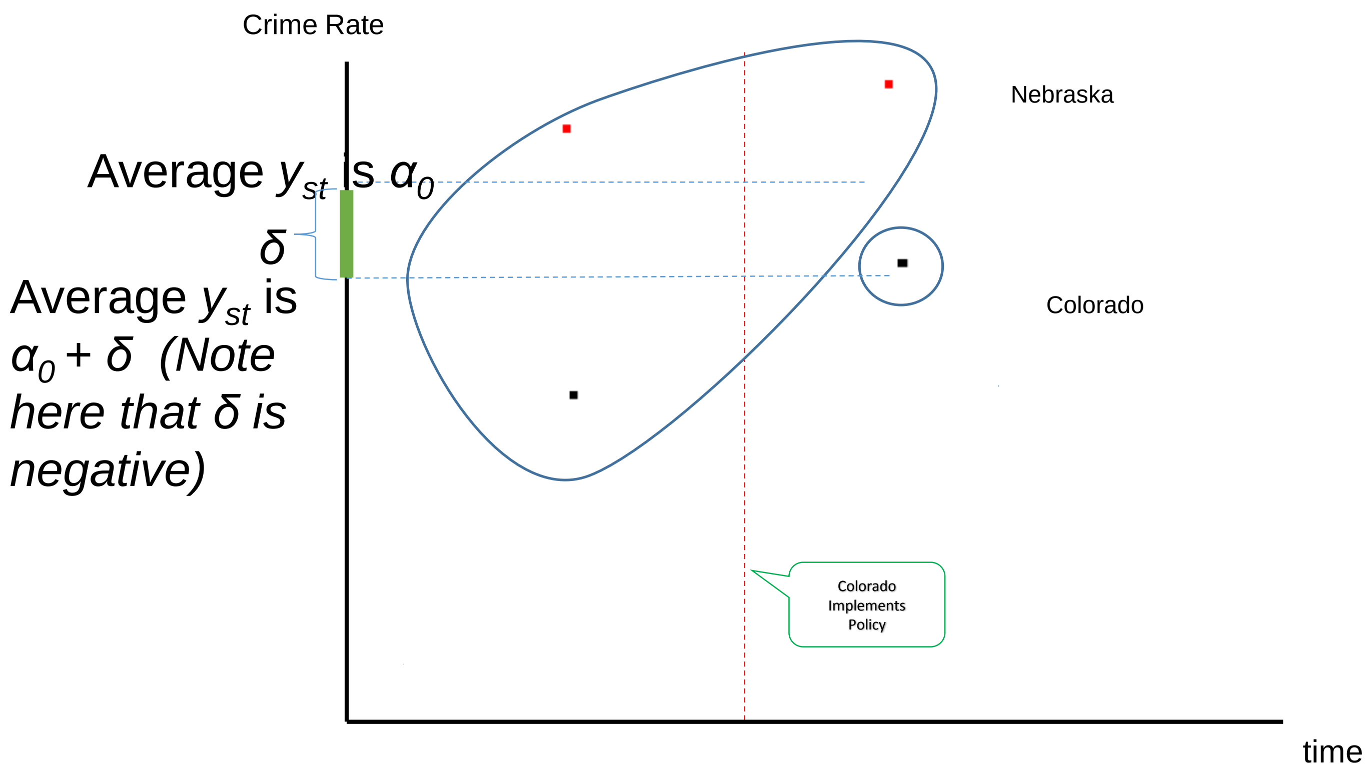


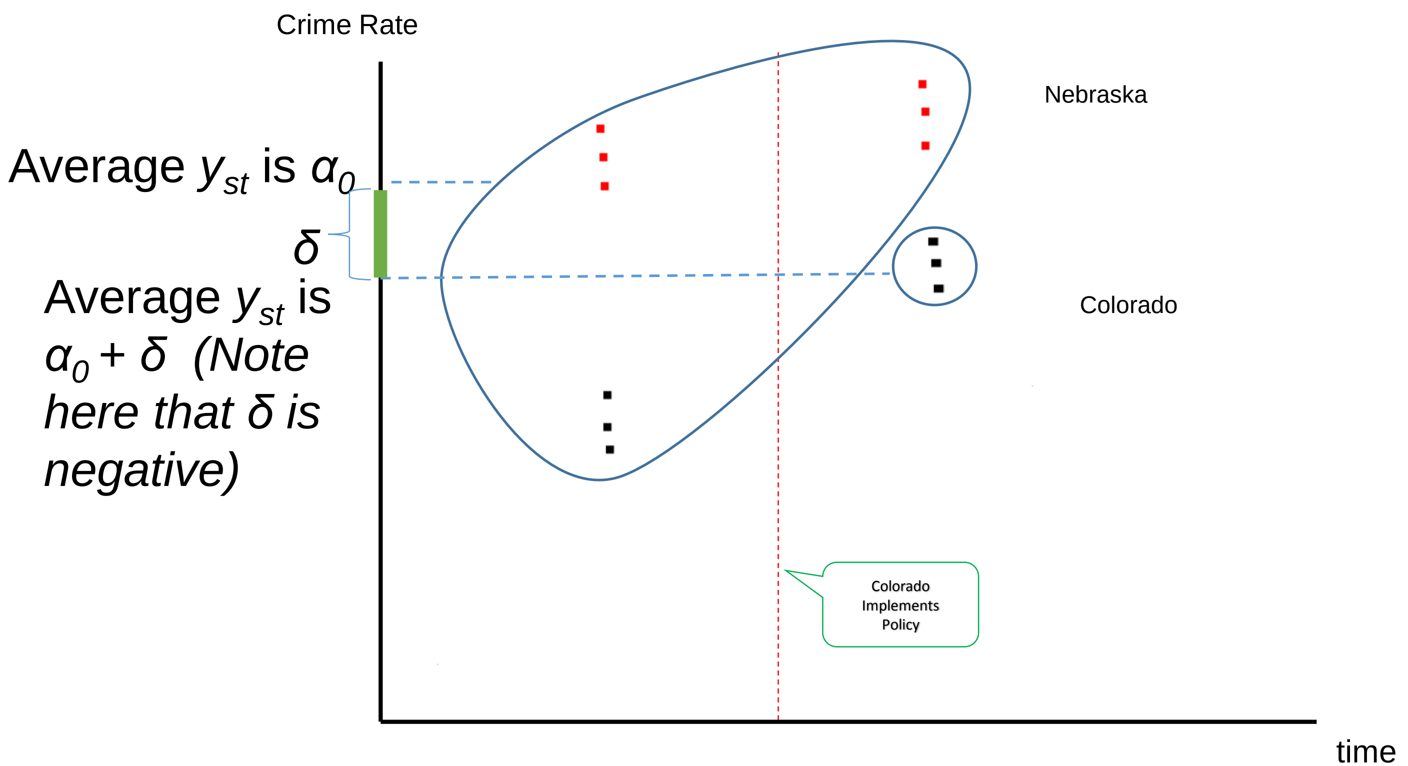
Difference in Difference Model with two states and two time periods. The estimating equation is:

$$y_{st} = \alpha_0 + \delta\ Treatment_s{*}Post_t + \varepsilon_{st}$$



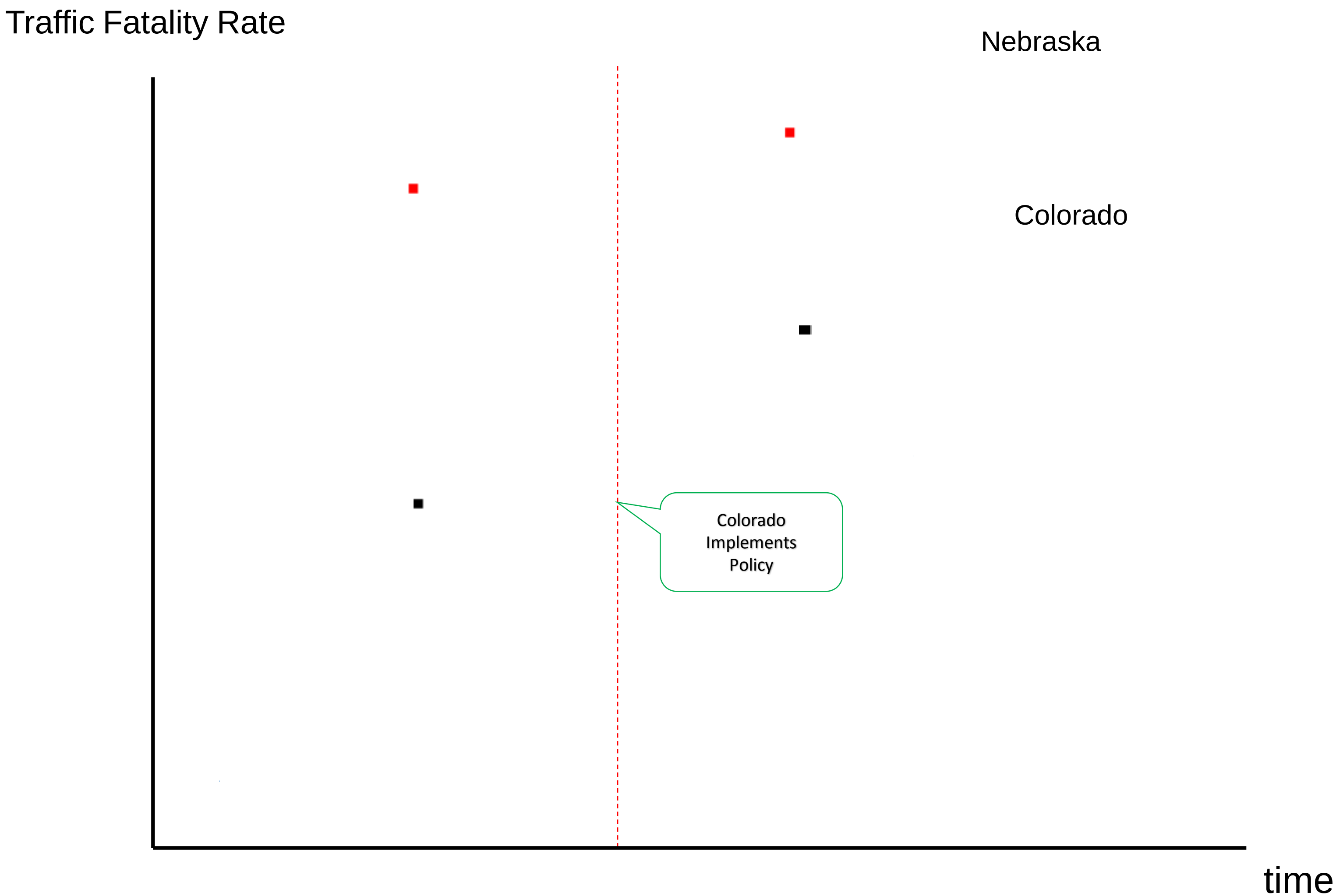
Suppose the estimating equation is:

$$y_{st} = \alpha_0 + \delta \, Treated_{st} + \varepsilon_{st}$$



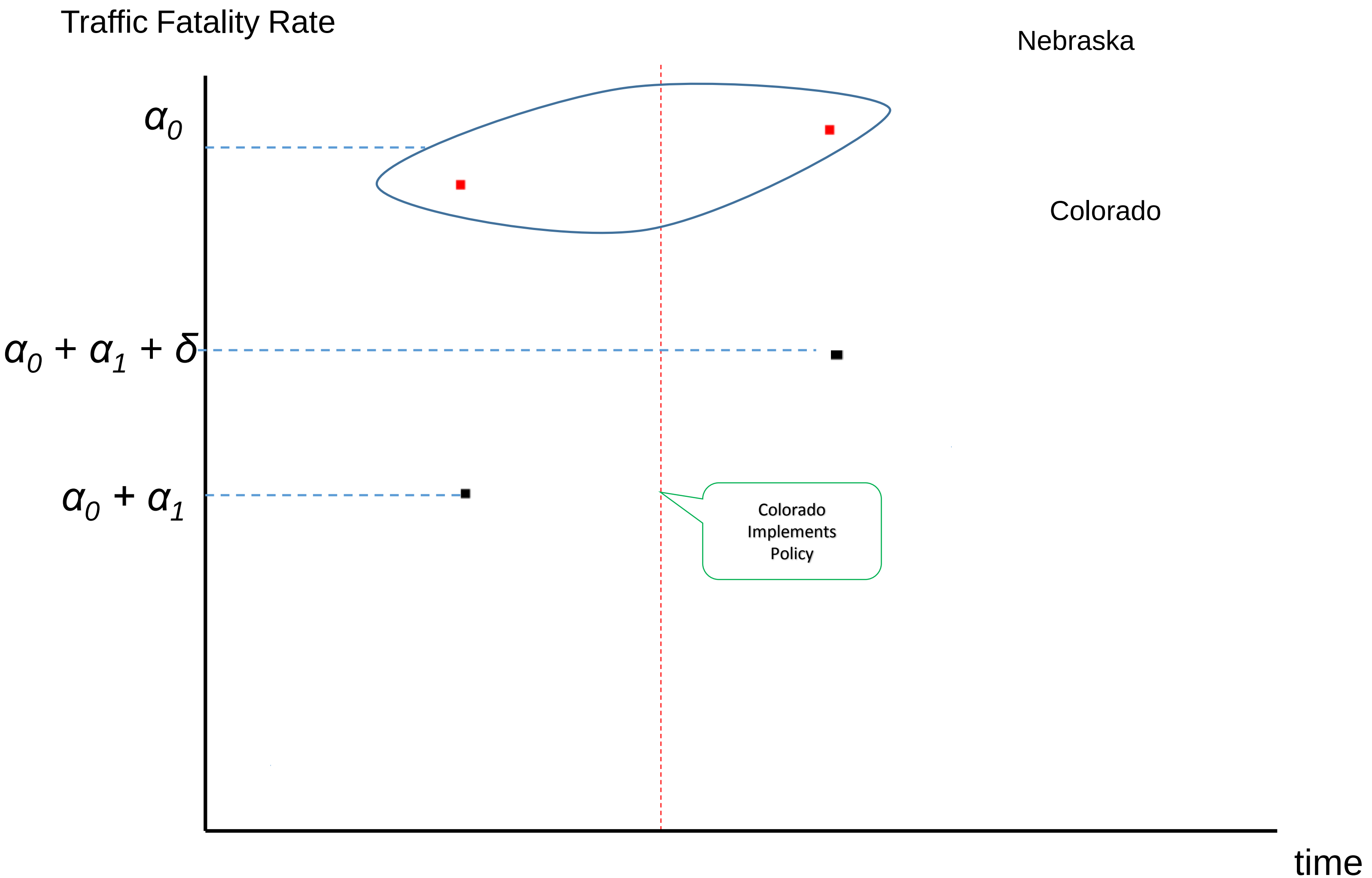
Multiple counties in the state. Suppose the estimating equation is:

$$y_{st} = \alpha_0 + \delta \, Treated_{st} + \varepsilon_{st}$$



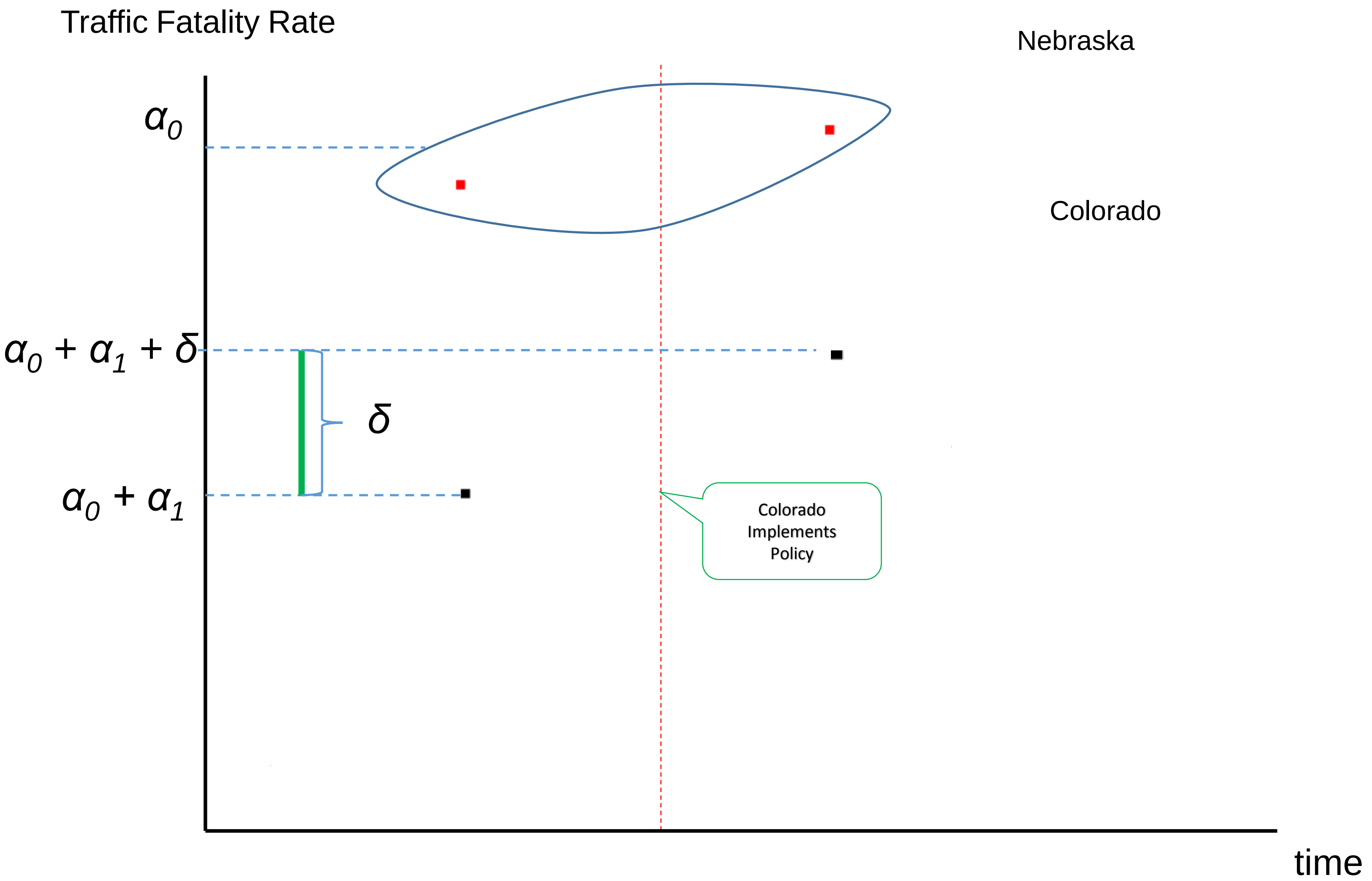
Difference in Difference Model with two states and two time periods. The estimating equation is:

$$y_{st} = \alpha_0 + \alpha_1 Treatment_s + \delta\ Treatment_s{*}Post_t + \varepsilon_{st}$$



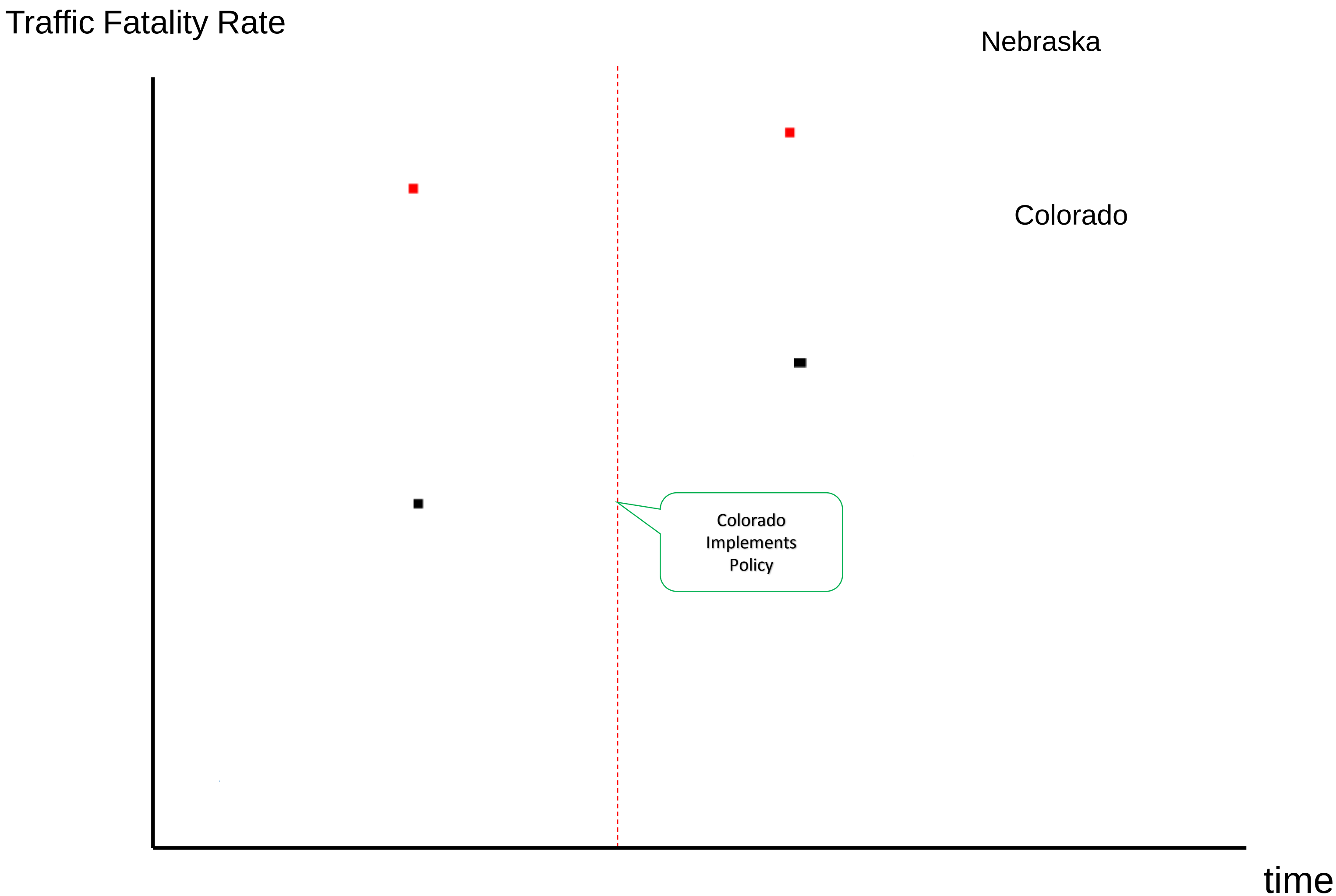
Difference in Difference Model with two states and two time periods. The estimating equation is:

$$y_{st} = \alpha_0 + \alpha_1 Treatment_s + \delta\ Treatment_s{*}Post_t + \varepsilon_{st}$$



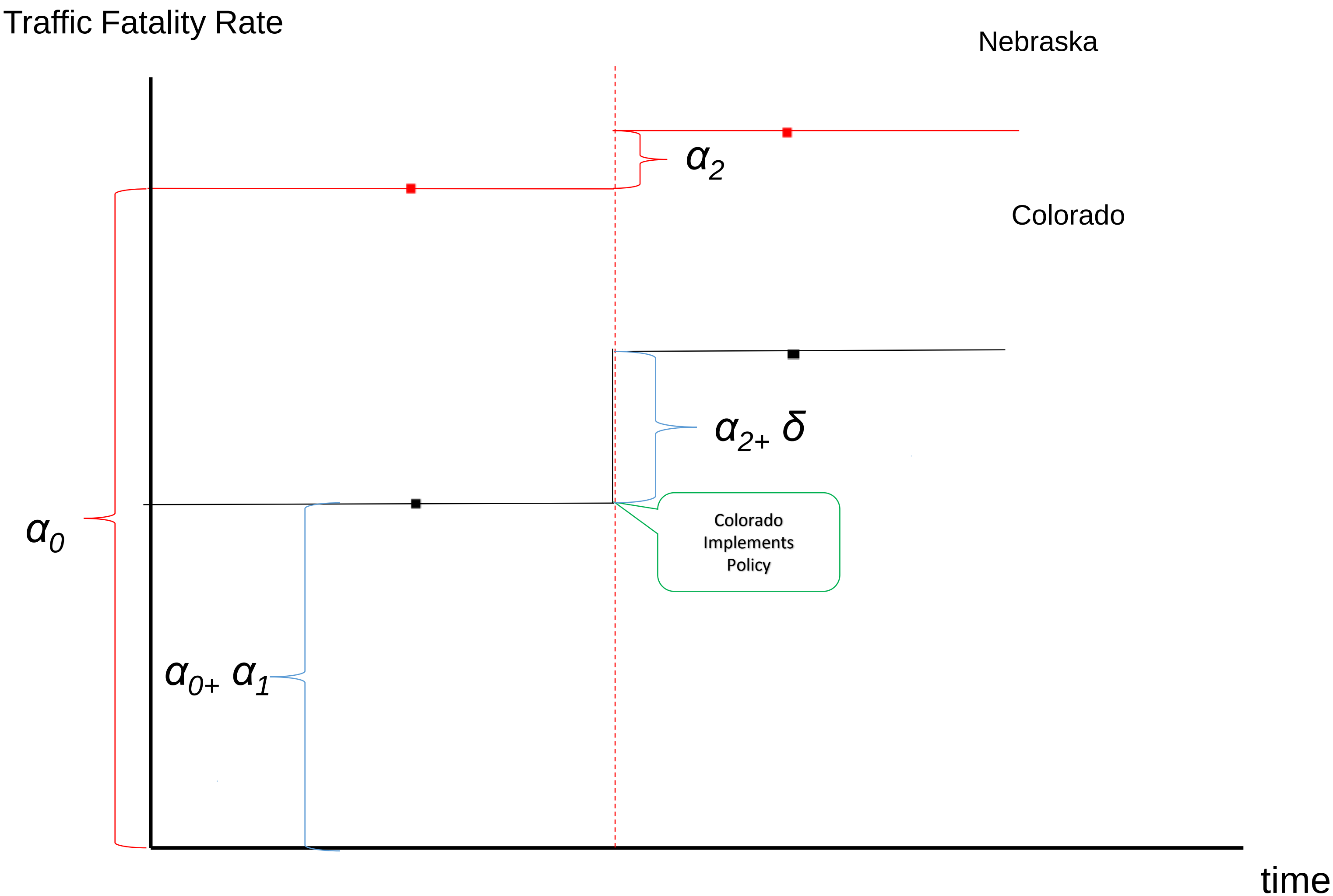
Difference in Difference Model with two states and two time periods. The estimating equation is:

$$y_{st} = \alpha_0 + \alpha_1 Treatment_s + \delta\ Treatment_s * Post_t + \varepsilon_{st}$$



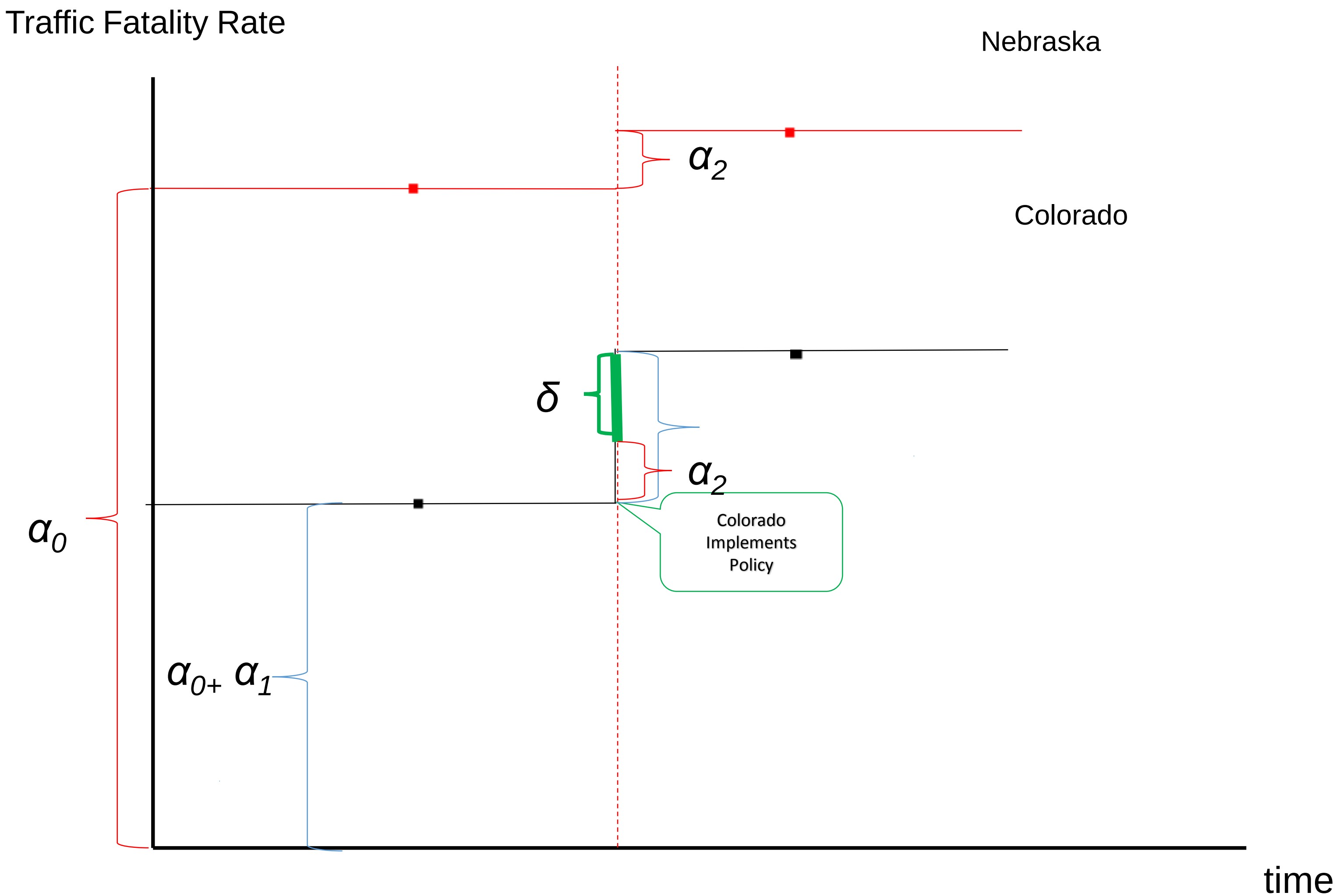
Difference in Difference Model with two states and two time periods. The estimating equation is:

$$y_{st} = \alpha_0 + \alpha_1 Treatment_s + \alpha_2 Post_t + \delta\, Treatment_s * Post_t + \varepsilon_{st}$$



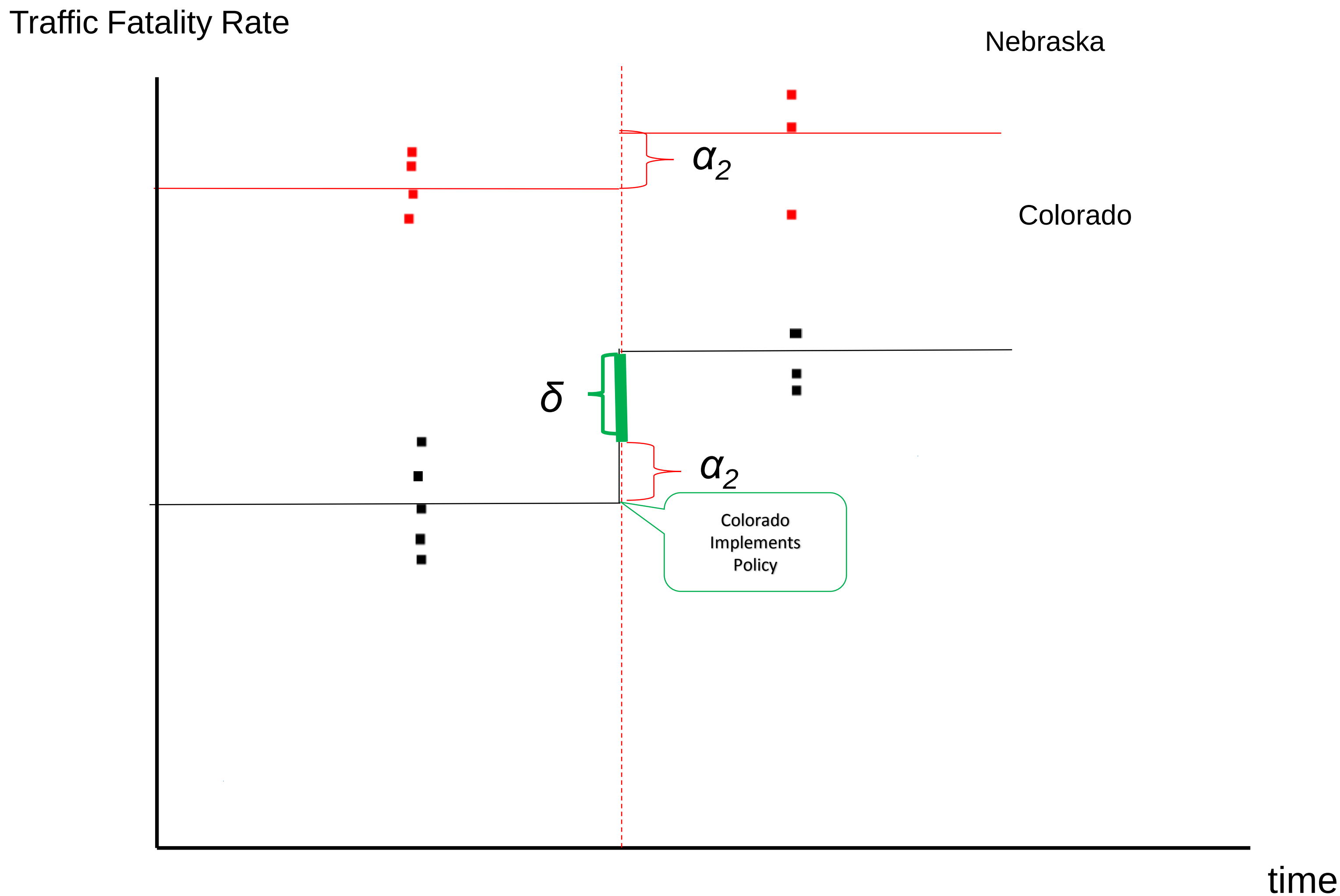
Difference in Difference Model with two states and two time periods. The estimating equation is:

$$y_{st} = \alpha_0 + \alpha_1 Treatment_s + \alpha_2 Post_t + \delta\ Treatment_s * Post_t + \varepsilon_{st}$$



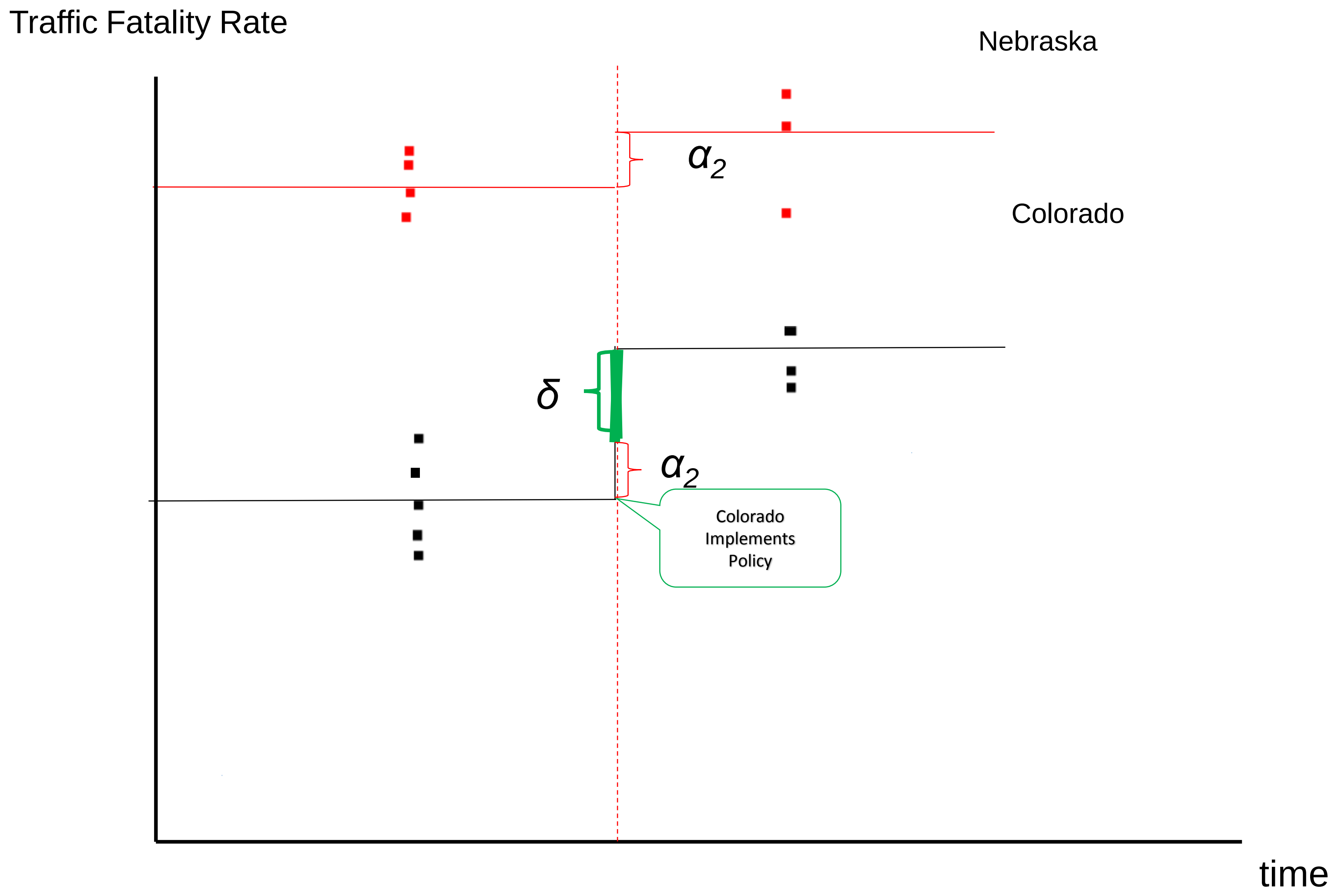
Difference in Difference Model with two states and two time periods. The estimating equation is:

$$y_{st} = \alpha_0 + \alpha_1 Treatment_s + \alpha_2 Post_t + \delta\ Treatment_s {*} Post_t + \varepsilon_{st}$$



Difference in Difference Model with two states and two time periods. Multple counties. The estimating equation is:

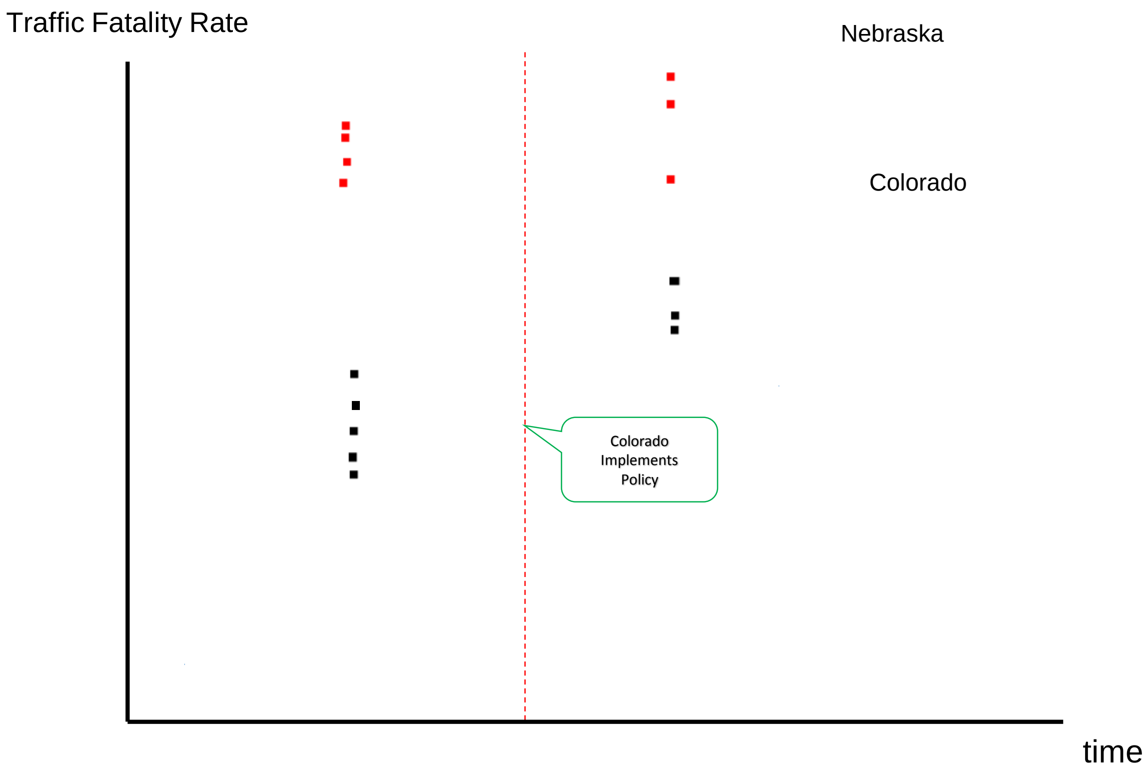
$$y_{st} = \alpha_0 + \alpha_1 Treatment_s + \alpha_2 Post_t + \delta\ Treatment_s * Post_t + \varepsilon_{st}$$



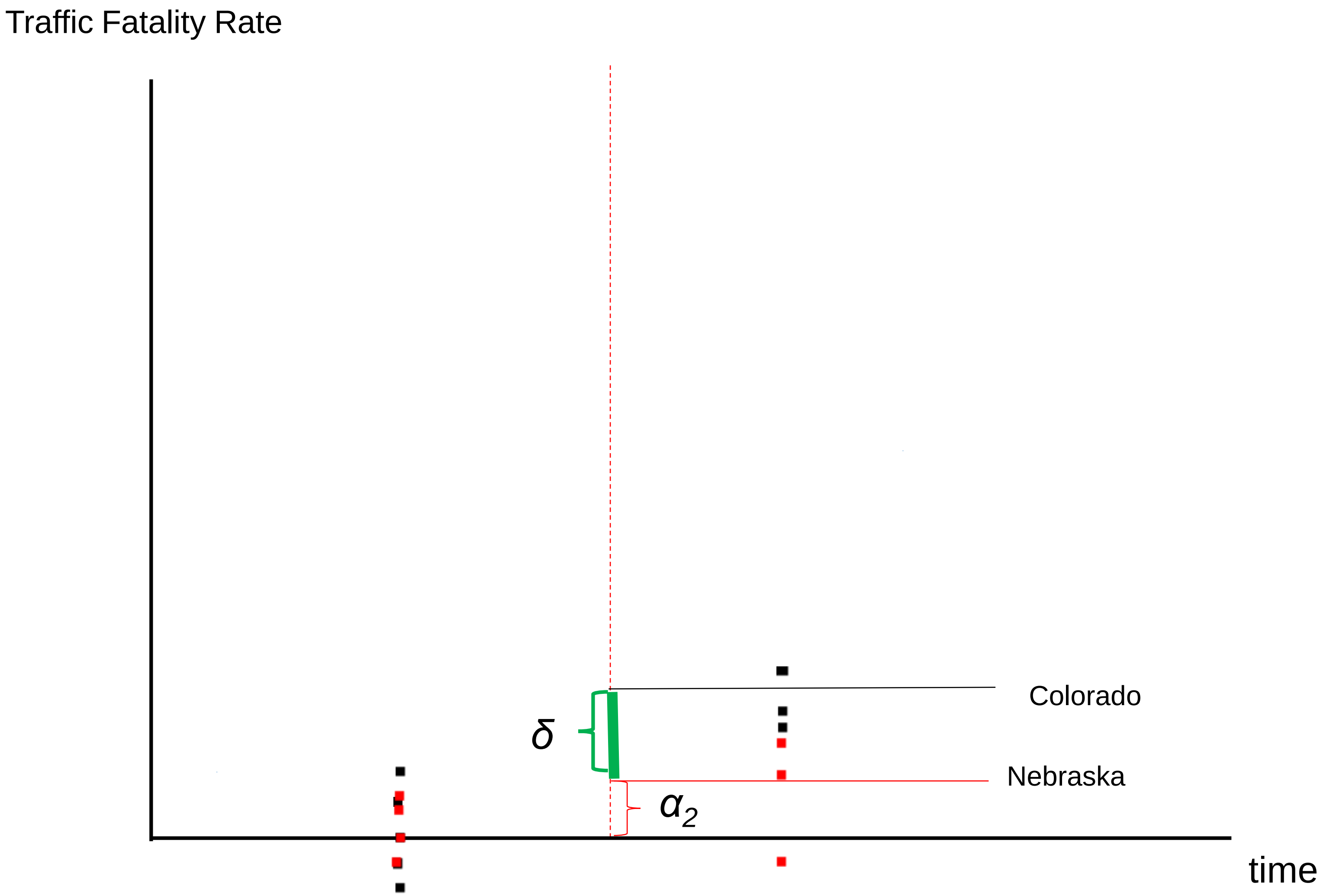
This estimating equation is exactly the same as:

$$y_{ist} = \alpha_0 + \alpha_1 dCO_s + \alpha_2 d2_t + + \delta\, Policy_{st} + \varepsilon_{ist}$$

dCO is dummy for CO; *d2* is dummy for year 2; *Policy* is dummy =1 in CO after policy is passed

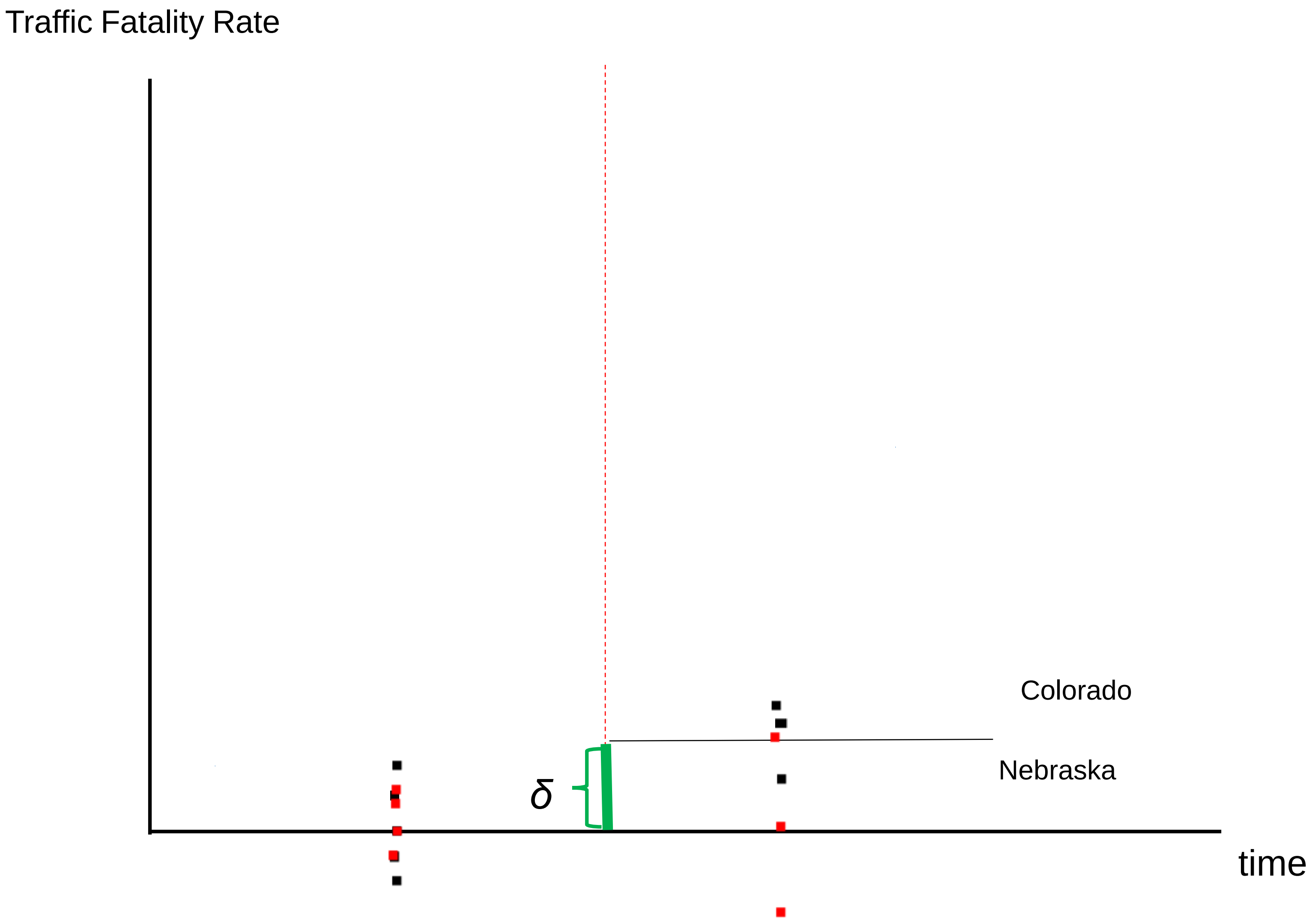


$$y_{ist} - \overline{y_s} = \alpha_2 d2_t + + \delta\ Policy_{st} + \varepsilon_{ist} - \overline{\varepsilon_s}$$



The estimate of δ is exactly the same as obtained by subtracting the mean for each state:

$$y_{ist} - \overline{y_s} = \alpha_2 d2_t + + \delta\ Policy_{st} + \varepsilon_{ist} - \overline{\varepsilon_s}$$



And δ is exactly the same after subtracting the mean for each time period:

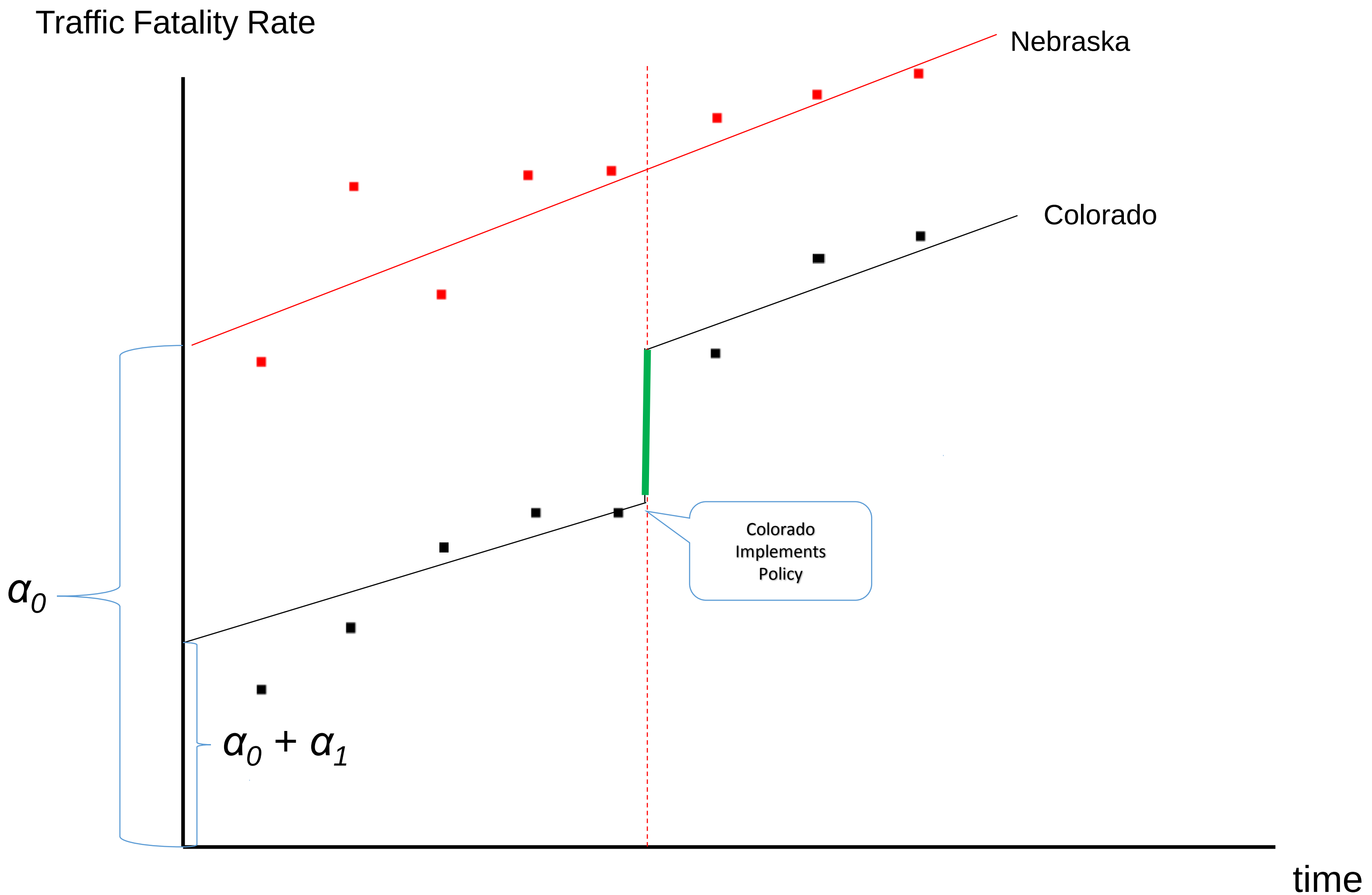
$$y_{ist} - \overline{y_s} - \overline{y_t} = \delta\ Policy_{st} + \varepsilon_{ist} - \overline{\varepsilon_s} - \overline{\varepsilon_t}$$

When we have lots of states and years, an author typically writes

$$y_{st} = \beta_0 + \delta Policy_{st} + v_s + z_t + \varepsilon_{st}$$

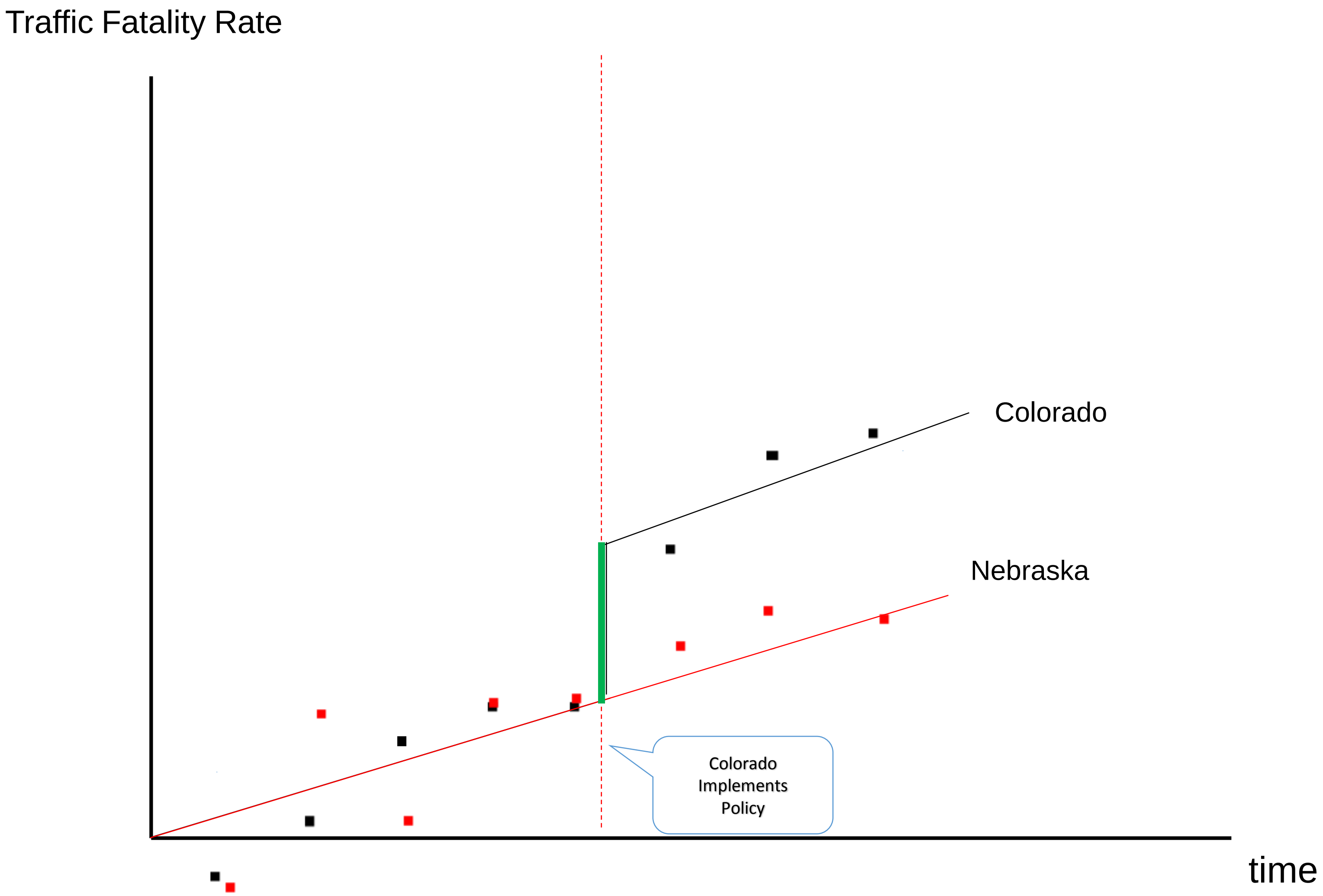
And then the author might say that the equation is estimated including state and year fixed effects

Start with state fixed effects, common time trend



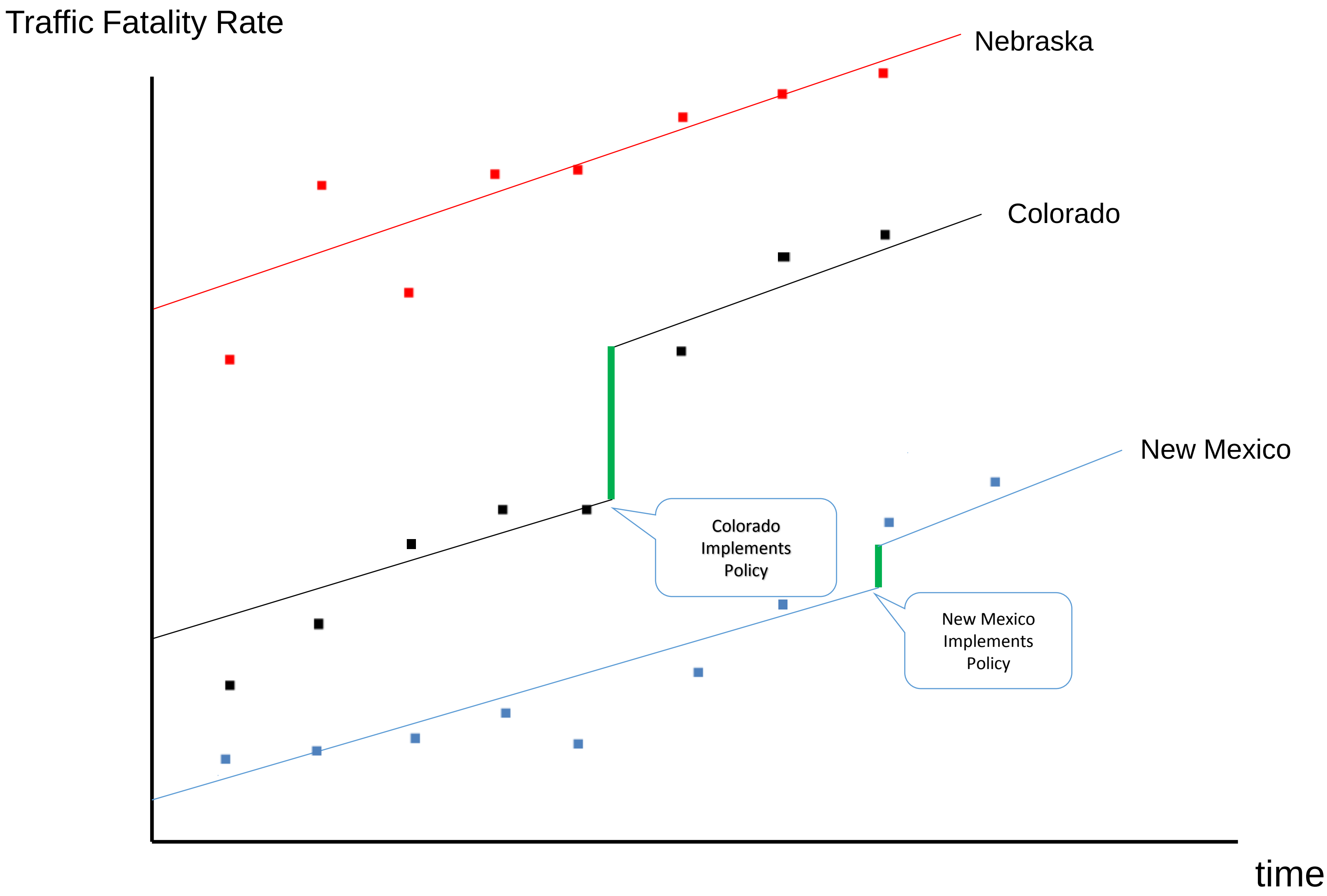
If we're using state-level data, then each state contributes one observation per year. The estimating equation with a common time trend is

$$y_{ist} = \alpha_0 + \alpha_1 dCO_s + \alpha_2 t + \delta\, Policy_{st} + \varepsilon_{ist}$$



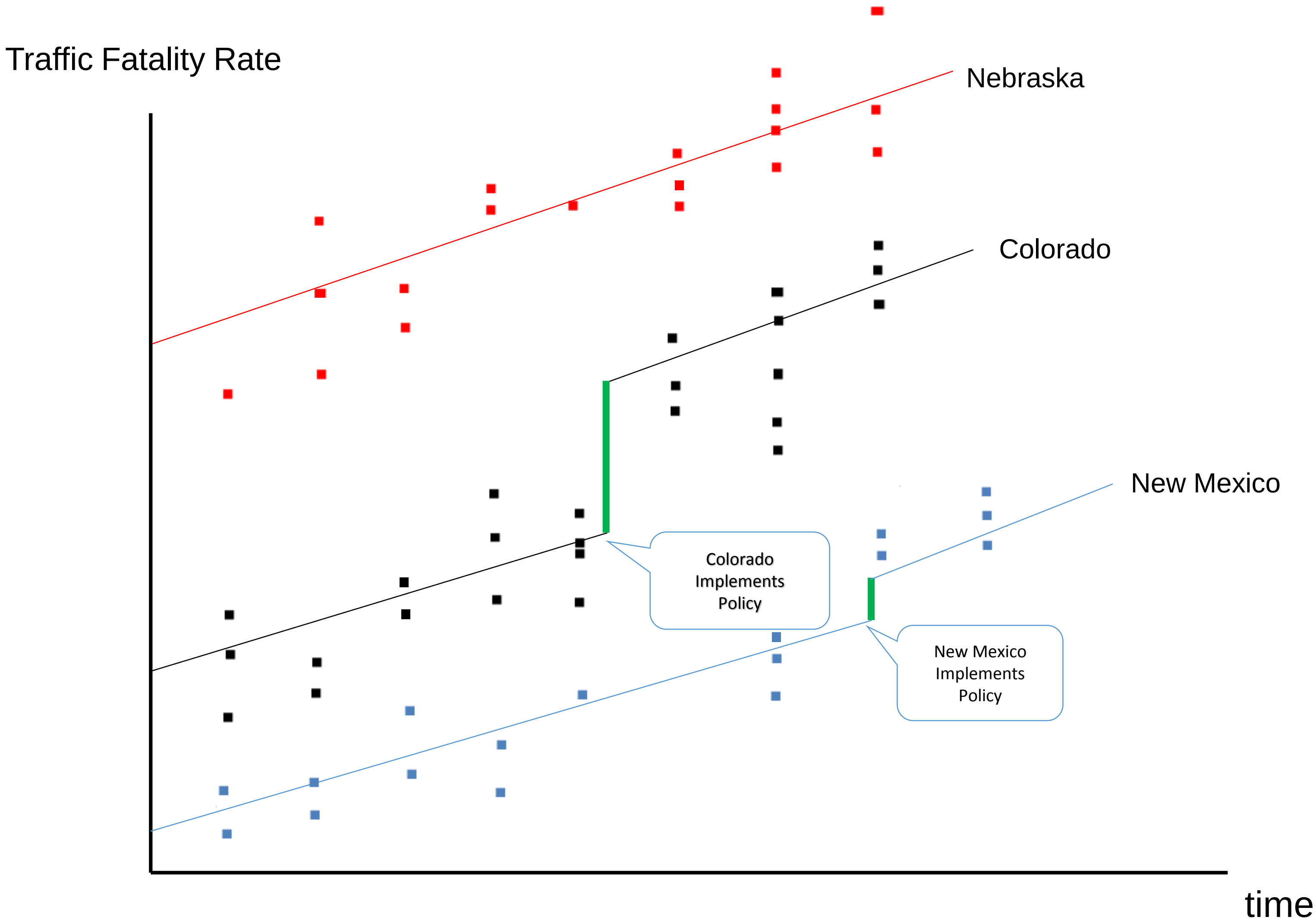
Remove state specific means→ δ will still be the vertical change

$$y_{ist} - \bar{y}_s = \alpha_2 t + \delta\, Policy_{st} + \varepsilon_{ist} - \bar{\varepsilon}_s$$



With multiple states δ will be the average vertical change across the states

$$y_{st} = \alpha_0 + \alpha_2 t + \delta Policy_{st} + v_s + \varepsilon_{st}$$



If we're using repeated cross-sectional data at the individual level, then each state contributes multiple observations per year. The estimating equation is:

$$y_{ist} = \alpha_0 + \delta\, Policy_{st} + \alpha_2 t + v_s + \varepsilon_{ist}$$

Pooled model: $MR_{it} = \beta_0 + \beta_1 unem_{it} + e_{it}$

id	state	year	murder rate				unem			
19	LA	87	11.1				12			
19	LA	90	17.2				6.2			
19	LA	93	20.3				7.4			
5	CA	87	10.6				5.8			
5	CA	90	11.9				5.6			
5	CA	93	13.1				9.2			

FD model: $\Delta MR_{it} = \beta_1 \Delta unem_{it} + \Delta\, e_{it}$

id	state	year	murder rate		ΔMR		unem	ΔUN		
19	LA	87	11.1		--		12	--		
19	LA	90	17.2		6.1		6.2	-5.8		
19	LA	93	20.3		3.1		7.4	1.2		
5	CA	87	10.6		--		5.8	--		
5	CA	90	11.9		1.3		5.6	-.02		
5	CA	93	13.1		1.2		9.2	3.6		

FE model: $MR_{it} - \overline{MR_i} = \beta_1 unem_{it} - \overline{unem}_i + e_{it}$

id	state	year	murder rate	Mean	MR-mean	unem	mean	UN-mean
19	LA	87	11.1	16.2	-5.1	12	8.5	3.5
19	LA	90	17.2	16.2	1	6.2	8.5	-2.3
19	LA	93	20.3	16.2	4.1	7.4	8.5	-1.1
5	CA	87	10.6	11.9	-1.3	5.8	6.9	-1.1
5	CA	90	11.9	11.9	0	5.6	6.9	-1.3
5	CA	93	13.1	11.9	1.2	9.2	6.9	2.3

The estimated coefficient on unemployment from these two models will be the same if there are only 2 years.

Otherwise, they are both consistent estimators of β_1 but their exact values will differ

FE model: $MR_{it} = \alpha_0 + \beta_1 unem_{it} + \alpha_1 State_i + e_{it}$

id	state	year	murder rate		unem		State
19	LA	87	11.1		12		1
19	LA	90	17.2		6.2		1
19	LA	93	20.3		7.4		1
5	CA	87	10.6		5.8		0
5	CA	90	11.9		5.6		0
5	CA	93	13.1		9.2		0

FE model: $MR_{it} = \alpha_0 + \beta_1 unem_{it} + \alpha_1 State_i + e_{it}$

id	state	year	murder rate	unem		State
19	LA	87	11.1	12		1
19	LA	90	17.2	6.2		1
19	LA	93	20.3	7.4		1
5	CA	87	10.6	5.8		0
5	CA	90	11.9	5.6		0
5	CA	93	13.1	9.2		0

The constant term in this model and the previous version of the FE model will be different (how?)

The estimated coefficient on unemployment WILL BE EXACTLY THE SAME

Can Labor Regulation Hinder Economic Performance? Evidence from India[1]

Timothy Besley and Robin Burgess

This paper investigates whether the industrial relations climate in Indian states has affected the pattern of manufacturing growth in the period 1958-92. We show that states which ammended the Industrial Disputes Act in a pro-worker direction experienced lowered output, employment, investment and productivity in registered or formal manufacturing. In contrast, output in unregistered or informal manufacturing increased. Regulating in a pro-worker direction was also associated with increases in urban poverty. This suggests that attempts to redress the balance of power between capital and labor can end up hurting the poor.

Our econometric analysis is based on panel data regressions of the form:

$$y_{st} = \alpha_s + \beta_t + \mu r_{st-1} + \xi x_{st} + \varepsilon_{st}$$

where y_{st} is a (logged) outcome variable in state s at time t, r_{st} is the regulatory measure (which we lag one period to capture the gap between enactment

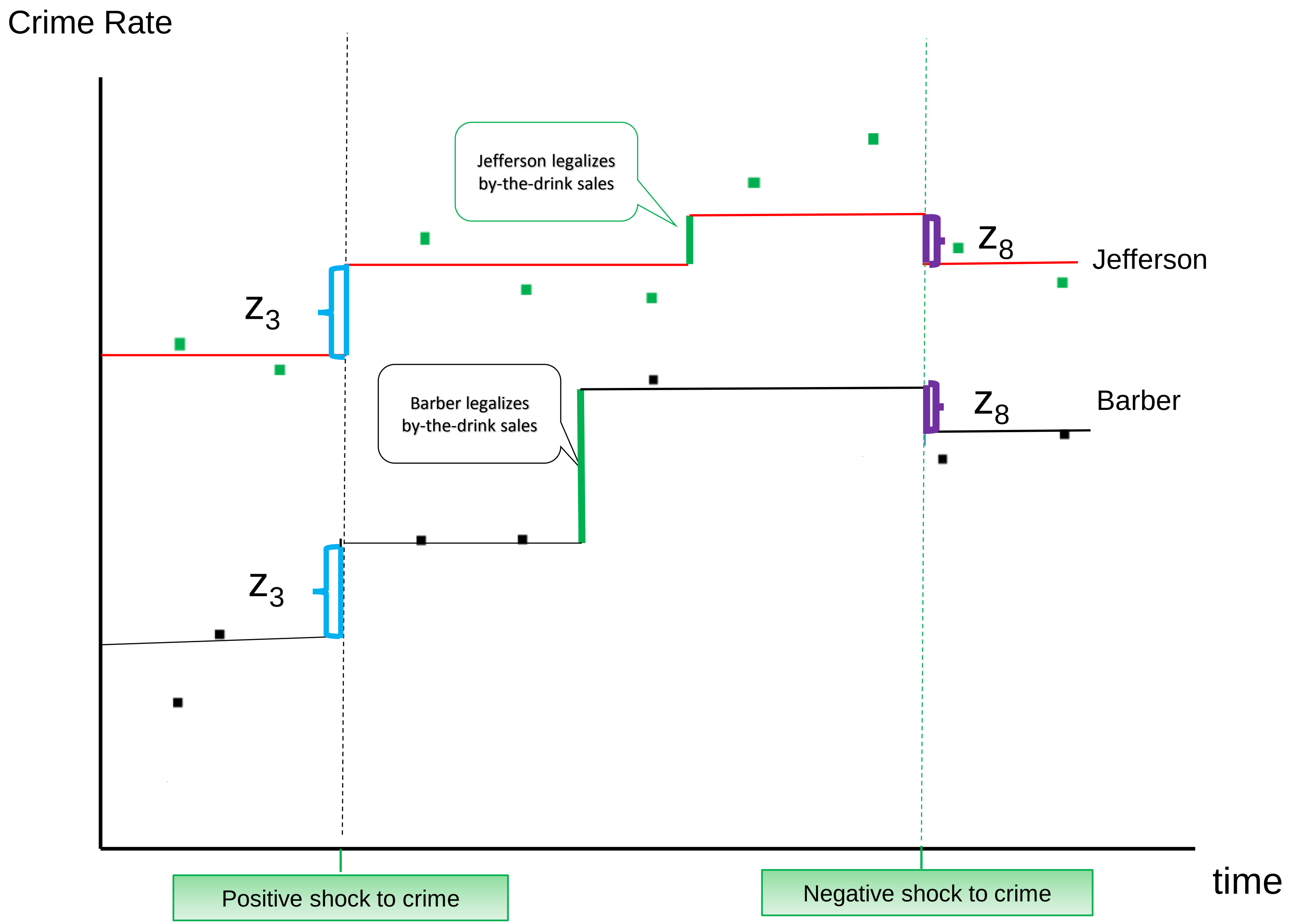
and implementation)[13], x_{st} are other exogenous variables, α_s is a state fixed effect and β_t is a year fixed effect. We cluster our standard errors by state to deal with concerns with serial correlation (Bertrand, Duflo and Mullainathan, [2002]).[14]

The state fixed effect captures state-specific factors such as culture and geography. The year effects capture common shocks such as central government amendments to the Industrial Disputes Act which took place in 1976 and 1982 (see Fallon [1987] and Fallon and Lucas [1993]) as well as other centrally implemented policies.

Now look at time shocks.

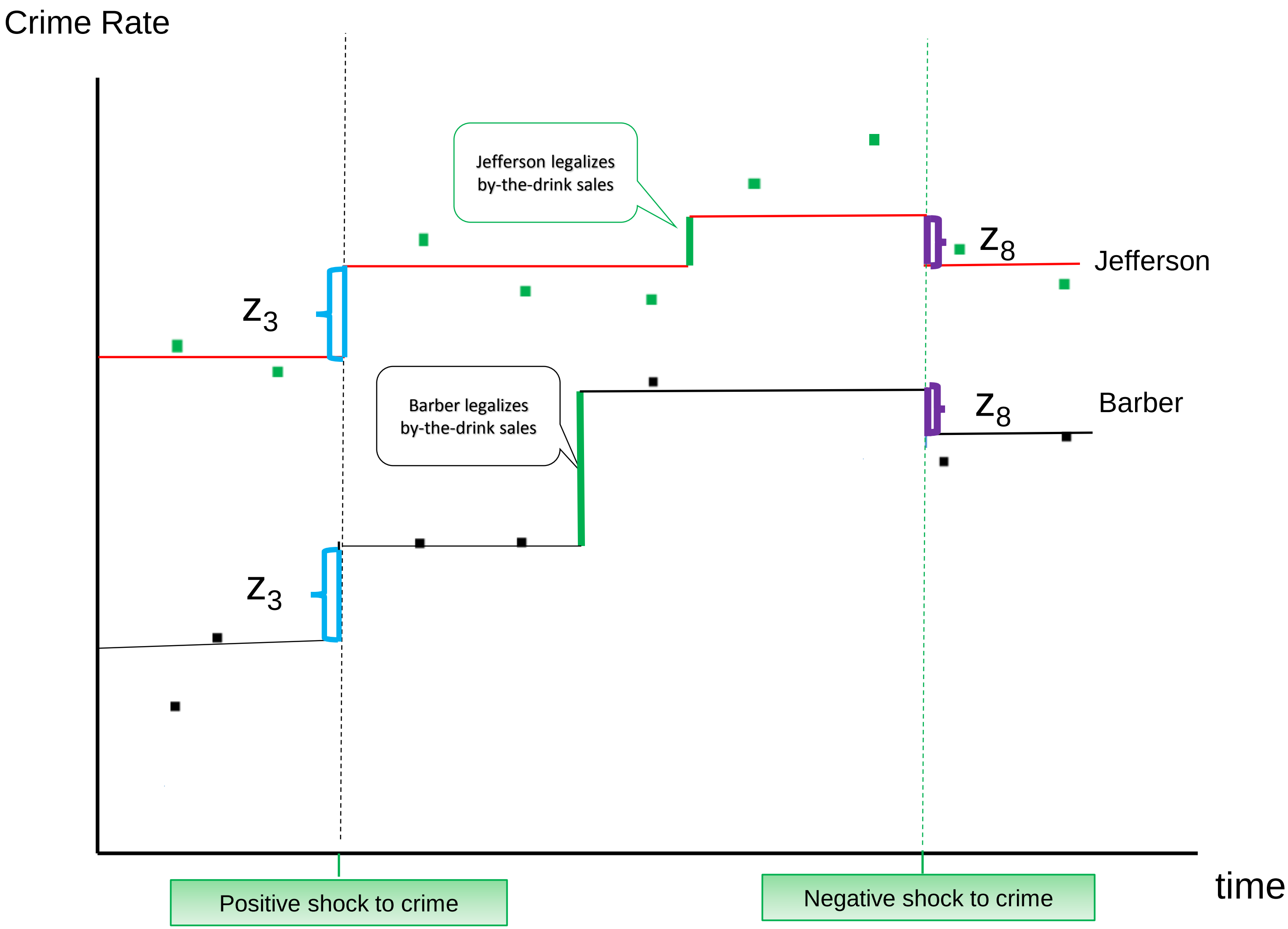
What if all states experience a common shock in a given year?

What if the means varies by time as well as by state?



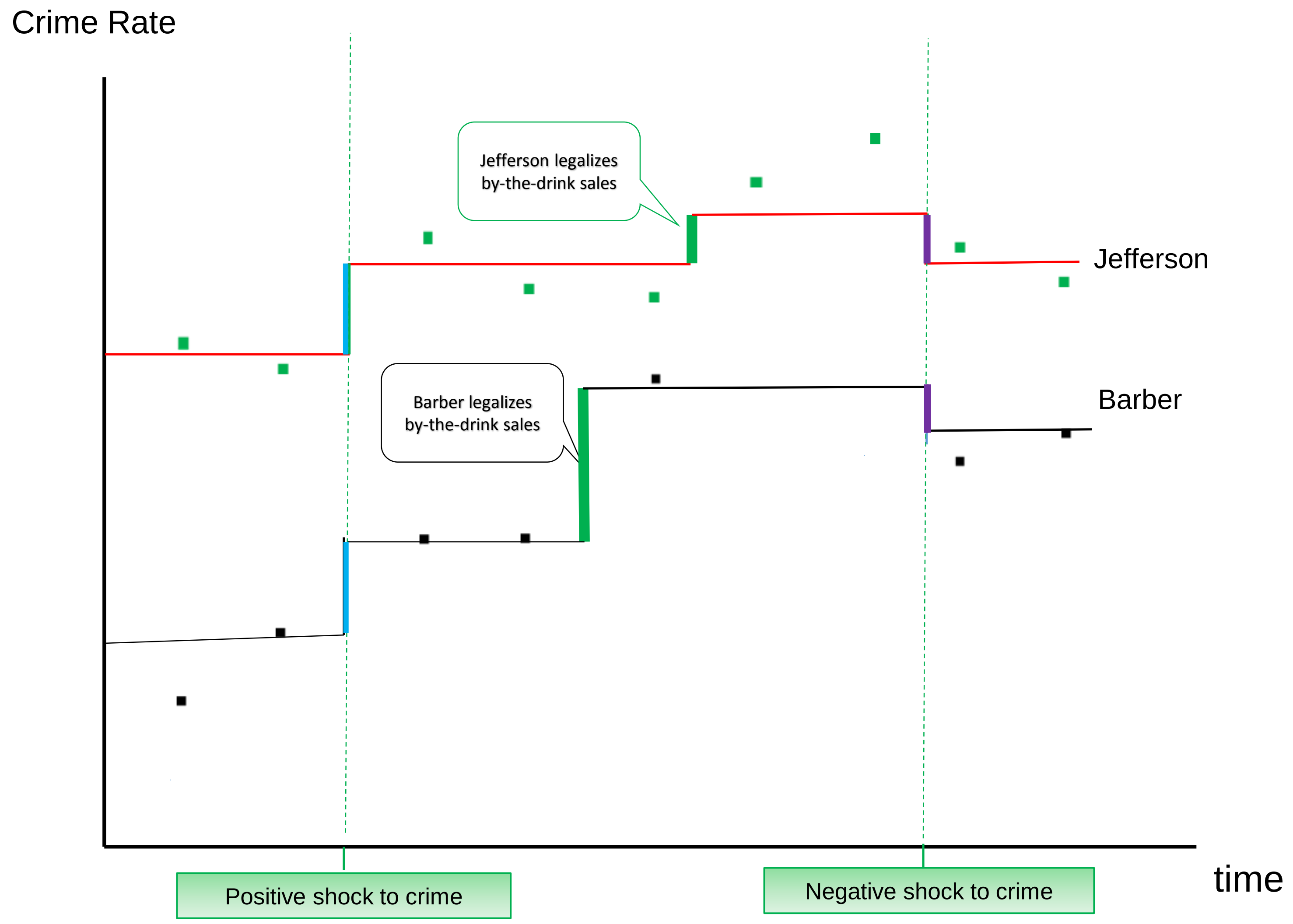
Common time fixed effects-- δ will still be the average vertical change from before and after the policy

$$Violent\ Crime_{ct} = \pi_0 + \delta\ Wet\ Law_{ct} + \boldsymbol{X'_{ct}\pi_2} + v_c + z_t + \varepsilon_{ct}$$



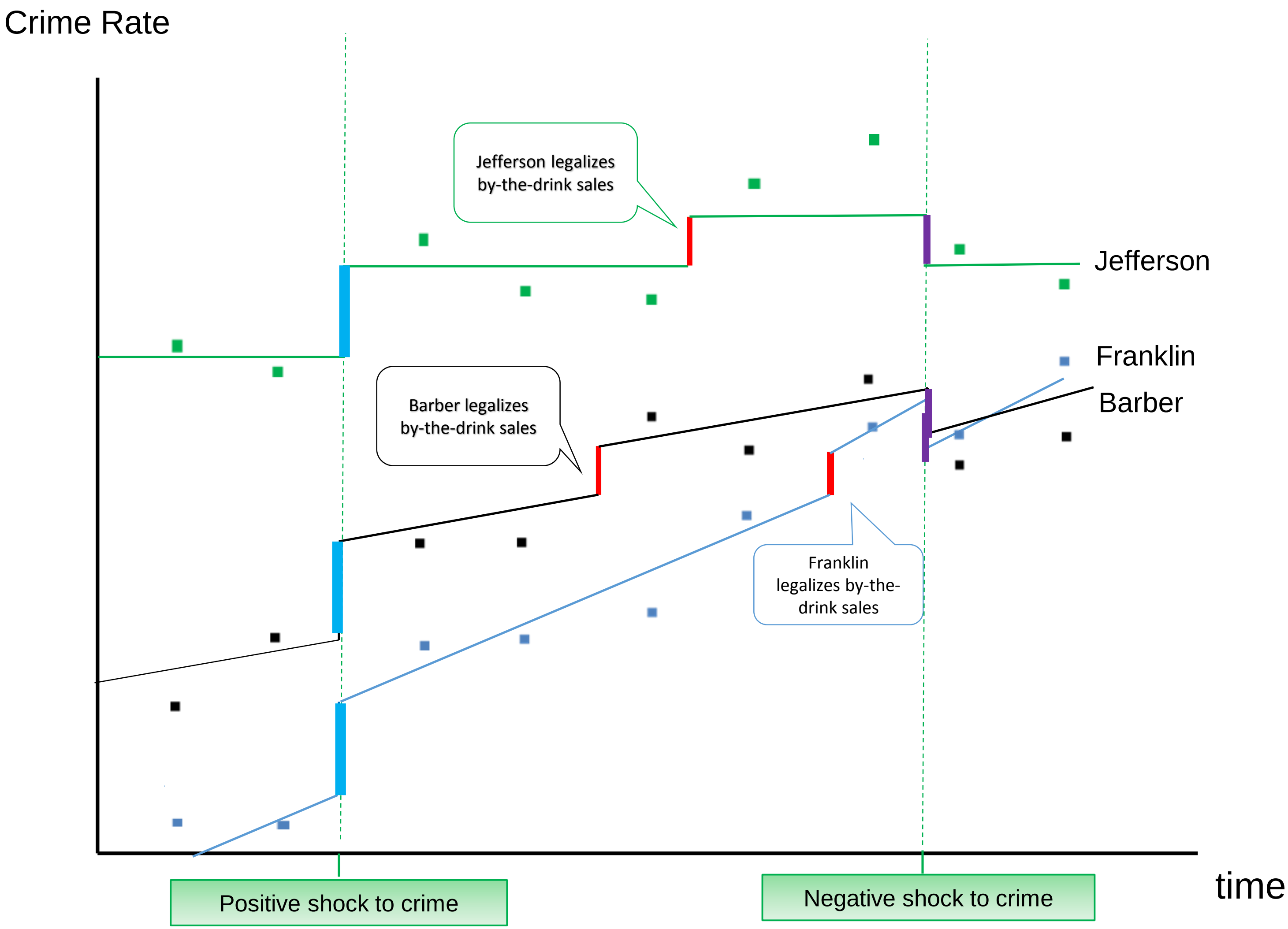
Common time fixed effects-- δ will still be the average vertical change from before and after the policy

$$\textit{Violent Crime}_{ct} = \pi_0 + \delta\ \textit{Wet Law}_{ct} + \boldsymbol{X}'_{ct}\boldsymbol{\pi}_2 + v_c + z_t + \varepsilon_{ct}$$



But note if you look at it, Barber is increasing faster than Jefferson:

$$Violent\ Crime_{ct} = \pi_0 + \pi_1 Wet\ Law_{ct} + \boldsymbol{X'_{ct}\pi_2} + v_c + z_t + \varepsilon_{ct}$$



Adding state specific time trends

$$Violent\ Crime_{ct} = \pi_0 + \delta\ Wet\ Law_{ct} + \boldsymbol{X'_{ct}\pi_2} + v_c + z_t + \Theta_c \cdot t + \varepsilon_{ct}$$

The fact that our results are not robust to state-specific time trends does raise the question of whether the effects that we are picking up are those due to labor regulations per se or the consequences of a poor climate of labor relations—union power and labor/management hostility—which affect the trend rate of growth within a state. This goes to interpretation of the finding. But either way, the analysis suggests that labor market institutions in India have had an important impact on manufacturing development.

The analysis reinforces the growing sentiment that government regulations in developing countries have not always promoted social welfare. The example that we have studied here is highly specific and it is clear that it cannot be used to promote a generalized pro- or antiregulation stance. Future progress will likely rest on improving our knowledge of specific regulatory policies. Research involving particular country experiences will be an important component of this. Only then can the right balance between the helping and hindering hands of government be found.