DiD strategies take into account the timing of the treatment (e.g., a policy shift) to obtain an estimate for the ATET.

Remember that we can write

$$Y_i = D_i Y_{i1} + (1 - D_i) Y_{i0}$$

= $Y_{i0} + D_i (Y_{i1} - Y_{i0})$
= $\alpha + \Delta_i D_i + \epsilon_i$

where $\alpha = \mu_0$ and $\epsilon_i = \mathbf{Y}_{i0} - \mu_0$.



To incorporate timing, let t_0 denote the time period before the assignement and t_1 , the time period after. We then append time subscripts to the above relation:

$$\mathbf{Y}_{it} = lpha + \Delta_i \mathbf{D}_{it} + \epsilon_{it}, t = t_1, t_0$$

where $\Delta_i = \mathbf{Y}_{i1t_1} - \mathbf{Y}_{i0t_1}$ and $\mathbf{D}_{it} = 0$ if $t = t_0$.

We can also decompose the shock ϵ_{it} as

$$m_t + \eta_i + v_{it}$$

where m_t is a macro shock affecting all equally at time *t* and η_i is a time-invariant individual effect.

The identifying assumption we will maintain here is that

$$E[\epsilon_{it}|\mathbf{D}_{it}] = m_t + E[\eta_i|\mathbf{D}_{it}]$$

which is equivalent to no selection on untreated outcomes (in first differences):

$$E[Y_{i0t_1} - Y_{i0t_0}|D_{it_1} = 1] = E[Y_{i0t_1} - Y_{i0t_0}].$$

This does not rule out selection on unobservables (since this may still depend on η_i).

It does exclude the possibility that selection is based on transitory individual-specific unobservables (v_{it}).



- Suppose for example that we want to evaluate a training programme for those with low earnings. Let the threshold for eligibility be *B*.
- We have a panel of individuals and those with low earnings qualify for training, forming the treatment group.
- ► Those with higher earnings form the comparison group.
- The treatment group may have low earnings for two reasons:
 - 1. They have low permanent earnings: η_i is low. This is handled by DiD.
 - 2. They have a negative transitory shock: v_{it} is low. This is *not* handled by DiD.



To see this note that participants are such that Y_{i0t₀} < B. Assume that the shocks v_{it} are *iid*. Then, v_{it₀} < B − α − m_{t₀} − η_i. this implies that

$$E[Y_{i0t_1} - Y_{i0t_0} | D_{it} = 1] = m_{t_1} - m_{t_0} - E[v_{it_0} | v_{it_0} < B - \alpha - m_{t_0} - \eta_i]$$

and for the comparison group

$$E[\frac{Y_{i0t_1} - Y_{i0t_0}|D_{it}}{D_{it}} = 0] = m_{t_1} - m_{t_0} - E[v_{it_0}|v_{it_0} > B - \alpha - m_{t_0} - \eta_i].$$

This implies that

$$E[Y_{i0t_1} - Y_{i0t_0} | D_{it} = 1] - E[Y_{i0t_1} - Y_{i0t_0} | D_{it} = 0] = E[v_{it_0} | v_{it_0} > B - \alpha - m_{t_0} - \eta_i] - E[v_{it_0} | v_{it_0} < B - \alpha - m_{t_0} - \eta_i] > 0$$



Ashenfelter (1978, REStat) was one of the first to consider DiD to evaluate training programs.

	White Males		Black Males		White Females		Black Females	
	Trainces	Comparison Group	Trainces	Comparison Group	Trainces	Comparison Group	Trainces	Comparison Group
1959 1960 1961 1962 1963 1964 1965 1966 1966 1968 1969	\$1,443 1,533 1,572 1,843 1,810 1,551 2,923 3,750 3,964 4,400 \$4,717	\$2,588 2,699 2,782 2,963 3,275 3,458 4,351 4,430 4,955 \$3,033	\$ 904 976 1,017 1,211 1,182 1,273 2,327 2,983 3,048 3,409 \$3,714	\$1,438 1,521 1,575 1,575 1,896 2,121 2,338 2,919 3,097 3,487 \$3,681	\$ 635 687 719 813 748 838 1,747 2,024 2,244 2,398 \$2,646	\$ 987 1,076 1,163 1,308 1,433 1,580 1,598 1,990 2,144 2,339 \$2,444	\$ 384 440 471 566 531 688 1,441 1,794 1,977 2,160 \$2,457	\$ 616 693 737 843 937 1,060 1,198 1,461 1,678 1,920 \$2,133
Number of Observations	7,326	40,921	2,133	6,472	2,730	28,142	1,356	5,192

TABLE L.—MEAN EARNINGS PRIOR, DURING, AND SUBSEQUENT TO TRAINING FOR 1964 MIDTA CLASSROOM TRAINIES AND A COMPARISON GROUP



With covariates, it is possible that

$$E[Y_{i0t_1} - Y_{i0t_0} | D_{it_1} = 1, X] = E[Y_{i0t_1} - Y_{i0t_0} | X]$$
even if

$$E[Y_{i0t_1} - Y_{i0t_0}|D_{it_1} = 1] \neq E[Y_{i0t_1} - Y_{i0t_0}].$$

This is just as in matching where the outcome now is the change in Ys!



Under the assumption that $E[Y_{i0t_1} - Y_{i0t_0}|D_{it_1} = 1] = E[Y_{i0t_1} - Y_{i0t_0}],$

$$\begin{aligned} ATET &= E[\Delta_i | D_{it_1} = 1] \\ &= E[\mathbf{Y}_{it_1} | D_{it_1} = 1] - E[\mathbf{Y}_{it_0} | D_{it_1} = 1] \\ &- \{E[\mathbf{Y}_{it_1} | D_{it_1} = 0] - E[\mathbf{Y}_{it_0} | D_{it_1} = 0]\}. \end{aligned}$$

Which suggests the empirical analog estimator

$$\widehat{ATET} = \frac{\sum_{i} d_{it_1}(y_{it_1} - y_{it_0})}{\sum_{i} d_{it_1}} - \frac{\sum_{i} (1 - d_{it_1})(y_{it_1} - y_{it_0})}{\sum_{i} (1 - d_{it_1})}$$

Notice this is just the within groups panel data estimator.



- If treatment and control groups can be separated before the policy change **and** composition of the groups with respect to the individual fixed effects does not change, repeated cross-section can be used to estimate the ATET.
- Differential macro trends would also invalidate the estimator.
- Selection on idiosyncratic shocks will also invalidate the estimator. One example is "Ashenfelter's dip". If enrolment to a training program is more likely when earnings are temporarily decreased, a faster earnings growth should be expected among the treated even without program participation.



To extend DiD to a nonlinear setting, suppose that

$$\mathbf{Y}_{it} = \mathbf{1}[\alpha + \Delta_i \mathbf{D}_{it} + \epsilon_{it} \ge \mathbf{0}].$$

As before, assume that

$$\epsilon_{it} = m_t + \eta_i - \mathbf{v}_{it}$$

and

$$\boldsymbol{E}[\epsilon_{it}|\boldsymbol{D}_{it}] = \boldsymbol{m}_t + \boldsymbol{E}[\eta_i|\boldsymbol{D}_{it}].$$

► Now, assume also that $v_{it} \sim F$ where *F* is known and $\eta_i = \eta_d$ if $D_{it} = d$.



- The above model corresponds to a binary response model with non-independent shocks.
- ► Under those parametric assumptions, letting Y^d_{it}, d = 0, 1 denote treated and untreated outcomes for individual *i* as before,

$$E[\mathbf{Y}_{it}^{0}|\mathbf{D}_{it_{1}} = d] = F(\alpha + \eta_{d} + m_{t})$$

$$\Rightarrow F^{-1}(E[\mathbf{Y}_{it}^{0}|\mathbf{D}_{it_{1}} = d]) = \alpha + \eta_{d} + m_{t}$$

for d = 0, 1 and $t = t_0, t_1$ since $E[\epsilon_{it}|D_{it}] = m_t + E[\eta_i|D_{it}]$.



► Then,

$$F^{-1}(E[Y^0_{it_1}|D_{it_1} = d]) - F^{-1}(E[Y^0_{it_0}|D_{it_1} = d]) = m_{t_1} - m_{t_0}$$
for $d = 0, 1$.

This leads to

$$E[\mathbf{Y}_{it_1}^0 | D_{it_1} = 1] = F(F^{-1}(E[\mathbf{Y}_{it_0}^0 | D_{it_1} = 1]) + \{F^{-1}(E[\mathbf{Y}_{it_1}^0 | D_{it_1} = 0]) - F^{-1}(E[\mathbf{Y}_{it_0}^0 | D_{it_1} = 0])\})$$



► The ATET (= $E[Y_{it_1}^1 - Y_{it_1}^0 | D_i = 1]$) can then be expressed as

$$\begin{aligned} \mathsf{ATET} &= E[\mathbf{Y}_{it_1}^1 | \mathbf{D}_{it_1} = 1] - F\Big(F^{-1}(E[\mathbf{Y}_{it_0}^0 | \mathbf{D}_{it_1} = 1]) \\ &+ \{F^{-1}(E[\mathbf{Y}_{it_1}^0 | \mathbf{D}_{it_1} = 0]) - F^{-1}(E[\mathbf{Y}_{it_0}^0 | \mathbf{D}_{it_1} = 0])\}\Big) \end{aligned}$$

An estimator for this quantity is

$$\widehat{ATET} = \frac{\sum d_i y_{it_1}}{\sum d_i} - F\left[F^{-1}\left(\frac{\sum d_i y_{it_0}}{\sum d_i}\right) + \left\{F^{-1}\left(\frac{\sum (1-d_i)y_{it_1}}{\sum (1-d_i)}\right) - F^{-1}\left(\frac{\sum (1-d_i)y_{it_0}}{\sum (1-d_i)}\right)\right\}\right]$$