

Master in Economics

Labour economics – Lecture 4

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Lisbon School
of Economics
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Universidade de Lisboa

Lecture 4

Topics:

- Supply of Labour to the Economy - The Decision to Work: Policy Application
 - Budget Constraints with “Spikes”
 - Programs with Net Wage Rates of Zero
 - Subsidy Programs with Positive Net Wage Rates
- Econometric methodology
 - Causal Inference: Estimation methods

Bibliography:

- Ehrenberg, Ronald & Robert Smith, Modern Labor Economics: Theory and Public Policy, Chapter 6
- Novo, Alvaro, Causal Inference: Estimation methods

Chapter 4: Supply of labour - The decision to work



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Chapter Outline

- **Policy Applications**
 - budget constraints with “Spikes”
 - programs with Net Wage Rates of Zero
 - subsidy programs with Positive Net Wage Rates

Policy Applications

- use labor supply theory to analyze the work-incentive effects of various social or income maintenance programs as they change budget constraints for their recipients

Policy Applications

- **Budget Constraints with “Spikes”**

e.g. Social insurance compensation programs that compensate workers for temporary work-related injuries, a permanent disability, or a layoff

- compensation insurance replaces earnings as long as the worker is off work
- programs pay benefits to those not working
- programs affect the work-incentives of workers since the returns associated with the first hour of work are usually negative – reduced income for returning to work for 1 hour

Policy Applications

- **Budget Constraints with “Spikes”**

e.g. A program that pay injured workers their pre-injury earnings for as long as they are off work and that once they work even one hour does not pay anything

- the spike creates severe work incentives problems:
 - the net wage associated with the first hour of work is clearly negative - the substitution effect associated with the program discourages work
 - allowing workers to achieve a higher utility while on benefits generates an income effect that discourages or at least slows return to work
 - the program raises the reservation wage above pre-injury level and so return to work only possible if the worker qualifies for a higher-paying job

Policy Applications: Budget Constraints with “Spikes”

Figure 6.13 Budget Constraint with a Spike

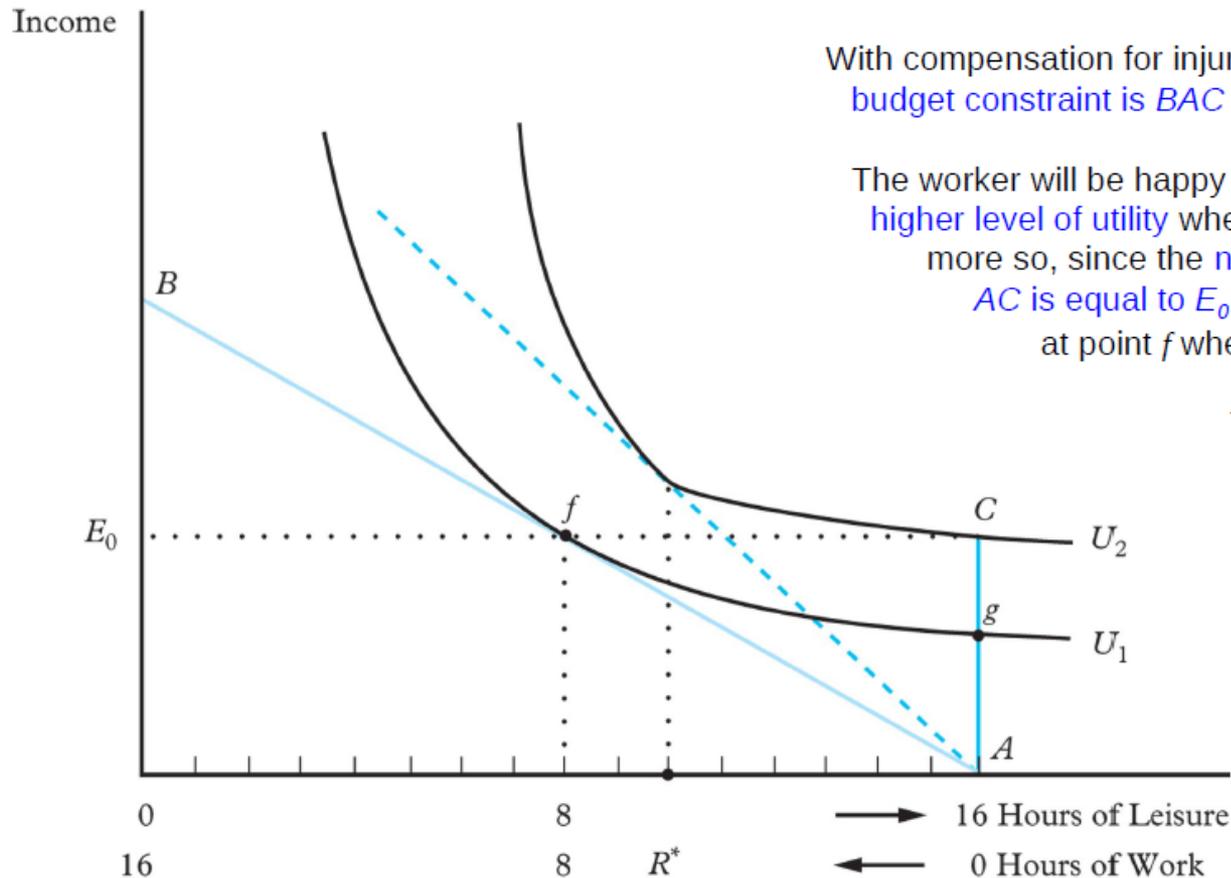
Pre-injury budget line $AB|_{W_{AB}}$ with earnings given as

$E_0 (= AC)$ at point f where $H = 8$ and $L = 8$.

With compensation for injury, the post-injury budget constraint is BAC with AC as the spike.

The worker will be happy to be at point C on a higher level of utility where $H = 0$ and $L = 16$, more so, since the no-work pay given by AC is equal to E_0 – the pre-injury pay – at point f where $H = 8$ and $L = 8$.

The income effect raises a worker's W_R (slope of the dashed line $> W_{AB}$) hence this slows his or her return to work.



Policy Applications: Budget Constraints with “Spikes”

- What can policymakers do to minimize the severe work disincentive problems associated to this type of programs?
 - set no-work benefits at some fraction of pre-injury earnings
 - set benefits at A_g so that a worker is on his or her pre-injury indifference curve but with earnings less than E_0 or set benefits slightly less than A_g (about half the pre-injury earnings) so that a worker will be eager to return to work as soon as he or she is physically able to do so
 - set an upper limit on the weeks the worker can receive the no-work benefits
 - if extensions are to be granted in some cases, set up a panel – medical or judicial board – to review such cases

Policy Applications

- **Programs with Net Wage Rates of Zero**
 - some social welfare programs calculate benefits based on the difference between one's actual earnings (Y_a) and one's needs (Y_n)
 - payment of benefits based on the difference between actual earnings and needs creates a net wage rate of zero
 - nature of welfare subsidies
 - determine the income needed (Y_n) based on:
 - family size
 - area living costs – *CPI*
 - local welfare regulations

Policy Applications: Programs with Net Wage Rates of Zero

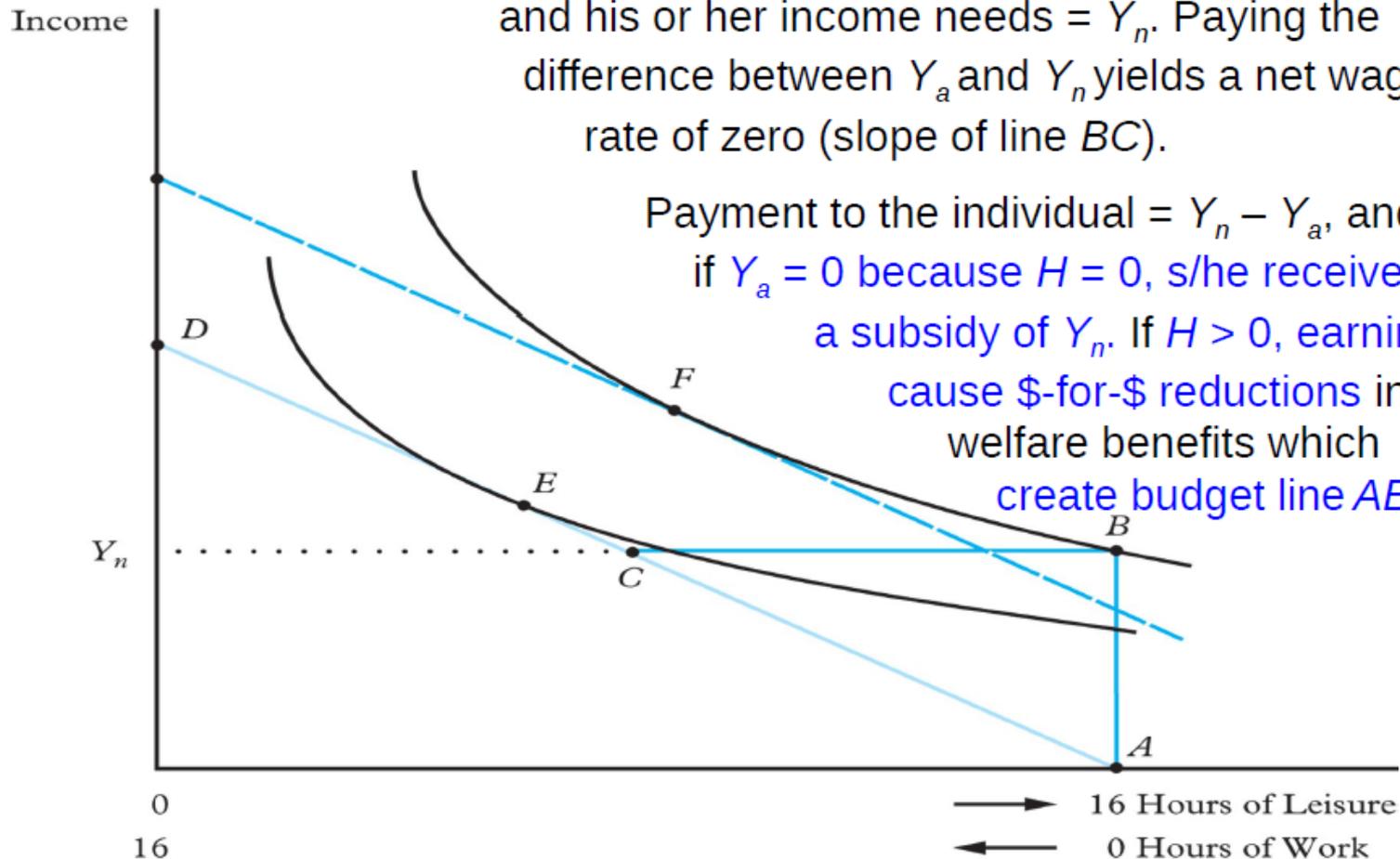
- for subsidy recipients, an extra hour of work yielded no net increase in income, because the extra earnings resulted in an equal reduction in welfare benefits – price of leisure was zero – the slope of line *BC*
- a welfare program that increases the income of the poor creates an income effect which tends to reduce labor supply as it also causes the wage to effectively drop to zero because every dollar earned is matched by a dollar reduction in welfare benefits
- the dollar-for-dollar reduction in benefits induces a huge substitution effect, which causes welfare recipients to reduce their hours of work to zero at point *B*

Policy Applications: Programs with Net Wage Rates of Zero

Figure 6.14 Income and Substitution Effects for the Basic Welfare System

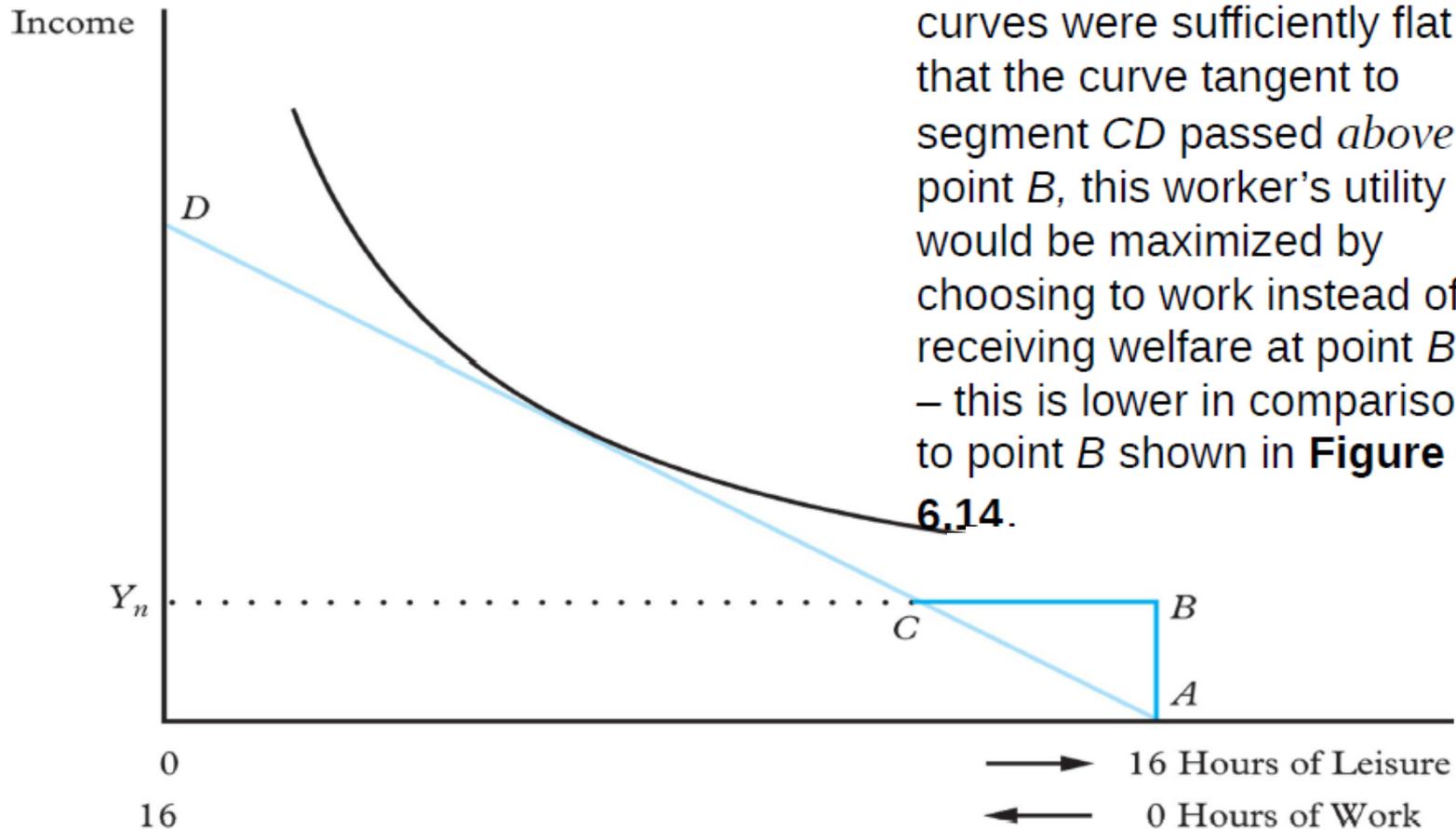
Let a worker's actual earnings = Y_a (at point E) and his or her income needs = Y_n . Paying the difference between Y_a and Y_n yields a net wage rate of zero (slope of line BC).

Payment to the individual = $Y_n - Y_a$, and if $Y_a = 0$ because $H = 0$, s/he receives a subsidy of Y_n . If $H > 0$, earnings cause \$-for-\$ reductions in welfare benefits which create budget line $ABCD$.



Policy Applications: Programs with Net Wage Rates of Zero

Figure 6.15 The Basic Welfare System: A Person Not Choosing Welfare



If a worker's indifference curves were sufficiently flat so that the curve tangent to segment CD passed *above* point B , this worker's utility would be maximized by choosing to work instead of receiving welfare at point B – this is lower in comparison to point B shown in **Figure 6.14**.

Policy Applications: Programs with Net Wage Rates of Zero

- **Welfare Reform - The United States made/adopted major changes to its income-subsidy programs in the 1990s because of the work disincentives inherent in the traditional welfare programs**
 - the Personal Responsibility and Work Opportunities Reconciliation Act (PRWORA) gave states more authority on how to design their own welfare programs:
 - encourage work
 - reduce poverty
 - move people off welfare

Changes appeared to have increased the LFPR of single mothers from 68% in 1994 to 78% in 2000

Policy Applications: Programs with Net Wage Rates of Zero

- **lifetime limits**
 - PRWORA placed a five-year lifetime limit on recipients:
 - reduce how long families could be on welfare
 - increase work incentives by eliminating income subsidy
 - potential welfare recipients must choose when to receive the subsidy and when to “save” their eligibility in the event of a future need
- **work requirements**
 - PRWORA of 1996 introduced a work requirement into the welfare system by requiring 6 hours of work per day (or at least 30 hours per week) after a recipient has been on welfare for two years
 - enrollment in education and training programs count toward work requirement
 - the work-incentive effects of the work requirement will depend on whether the indifference curves are steeply sloped or flatly sloped

Policy Applications: Programs with Net Wage Rates of Zero

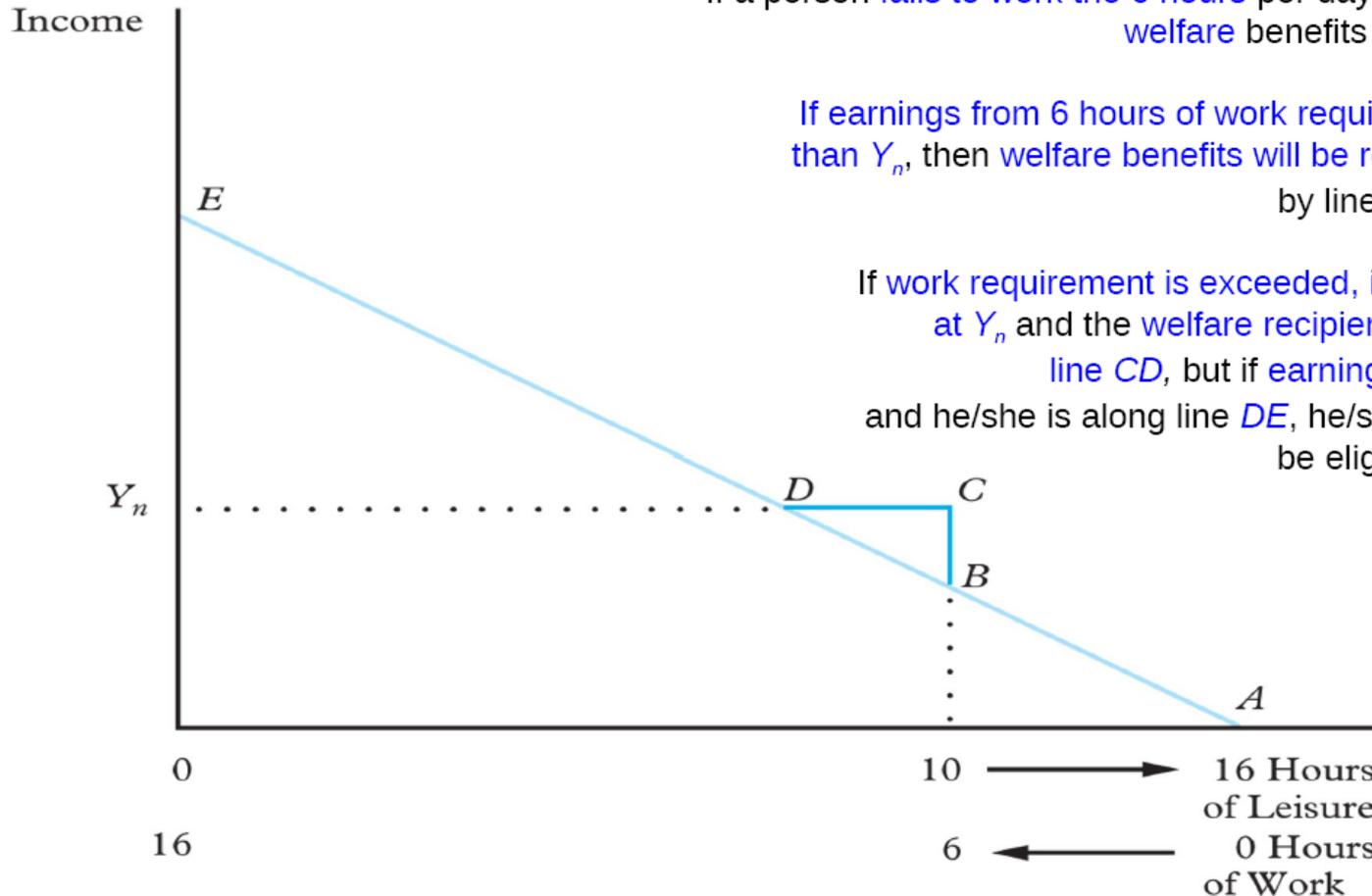
Figure 6.16 The Welfare System with a Work Requirement

Work requirement = 6 hours per day (or 30 hours per week).

If a person fails to work the 6 hours per day as required, no welfare benefits will be received.

If earnings from 6 hours of work requirement are less than Y_n , then welfare benefits will be received (given by line segment BCD).

If work requirement is exceeded, income remains at Y_n and the welfare recipient will be along line CD , but if earnings rise above Y_n and he/she is along line DE , he/she will no longer be eligible for welfare.



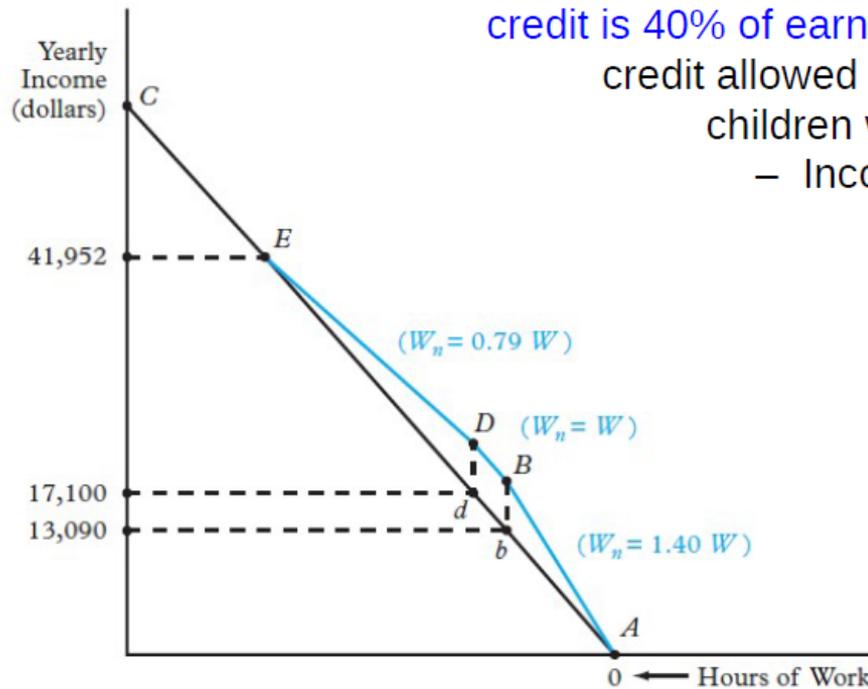
Policy Applications

- **Subsidy Programs with Positive Net Wage Rates: The Earned Income Tax Credit (EITC)**
 - an income maintenance program - functions as an earnings (cash) subsidy, which goes only to those who work.
 - the tax credit offered by the EITC programs varies with one's earnings and the number of dependent children.

Policy Applications: Subsidy Programs with Positive Net Wage Rates

Figure 6.17 Earned Income Tax Credit (Unmarried, Two Children), 2012

- The EITC as an earnings subsidy creates a budget constraint of *ABDEC*.
 - For workers with earnings of \$13,090 or less, the tax credit is 40% of earnings, and the maximum tax credit allowed for a single parent with two children was \$5,236 in 2012.
 - Incomes between \$13,090 and \$17,100 qualify for the maximum tax credit:
 - Line *AB* = \$18,326
 - Line *AD* = \$22,336.
 - Earnings of \$41,952 and above do not qualify for this tax credit.



Policy Applications: Subsidy Programs with Positive Net Wage Rates

- **EITC recipients could experience:**
 - an income effect that pushes them in the direction of less work – those whose annual income falls between \$13,090 and \$41,952
 - a substitution effect that pushes the recipients in the direction of more work, thus the labor force participation of low-income workers will increase – those whose annual income is less than \$13,090

*Econometric methodology: Causal
Inference and Estimation methods*



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Fundamental identification problem

- In most labour market analysis, one tries to measure the effect of a “treatment” – to measure the causal effect of the “treatment” on a specific outcome
- Y_i : outcome variable for unit i
- $D_i = 1$ if unit i is treated and $D_i = 0$ if unit i is not treated
- Two potential outcomes
 - Y_{0i} : Potential outcome without treatment for unit i
 - Y_{1i} : Potential outcome with treatment for unit i
- The causal effect of the treatment for unit i :

$$Y_{1i} - Y_{0i}$$

Fundamental problem of identification:
Cannot observe both Y_{0i} and Y_{1i} for the same individual

Fundamental identification problem

- Only observe the realized outcome Y_i :
 - Y_{1i} if $D_i = 1$
 - Y_{0i} if $D_i = 0$
- Homogeneity of statistical units would solve this problem... but heterogeneity rules
- Even if we cannot compute individual treatment effects, we want to compute average effects
 - Average treatment effect (ATE): $\alpha_{ATE} = E[Y_1 - Y_0]$
 - Average treatment effect on the treated (ATET): $\alpha_{ATET} = E[Y_1 - Y_0 | D=1]$

Fundamental identification problem

- Problem: comparisons between treated and untreated do not usually give the right answer:

$$\begin{aligned} E[Y | D = 1] - E[Y | D = 0] &= E[Y_1 | D = 1] - E[Y_0 | D = 0] \\ &= E[Y_1 - Y_0 | D = 1] + \{E[Y_0 | D = 1] - E[Y_0 | D = 0]\} \end{aligned}$$

ATET bias

Bias term is not likely zero: selection problems. Participation is usually associated with the potential outcome

- Solution: Study the assignment mechanism (*and restrict it appropriately*)

Fundamental identification problem

- **Possible solutions**
 - Randomized experiments
 - **Observational studies**
 - Matching estimators: Matching on covariates
 - Regression
 - Difference-in-Differences

Randomized experiences

- If treatment is independent of potential outcomes, then treatment is ignorable

$$E[Y_0|D = 1] = E[Y_0|D = 0]$$

$$\alpha_{ATET} \equiv E[Y_1 - Y_0|D = 1] = E[Y | D = 1] - E[Y | D = 0]$$

and

$$\alpha_{ATE} \equiv E[Y_1 - Y_0] = E[Y_1 - Y_0|D = 1] = E[Y | D = 1] - E[Y | D = 0]$$

$$\text{(because } E[Y_1|D = 1] = E[Y_1|D = 0]\text{)}$$

Randomized study forces (Y_1, Y_0) to be independent on treatment and then $\alpha_{ATET} = \alpha_{ATE}$

Randomized experiences

- Predetermined observed characteristics (e.g. age, sex, education) should be balanced between treated and controls
- Unobserved characteristics (e.g. ability) are also balanced

$$\hat{\alpha} = \overline{Y_1} - \overline{Y_0}$$

Randomized experiences

- **Validity and threats**

- **Internal validity: the study allows to estimate the effect for our sample with minimum bias?**
 - Failure of randomization
 - Non-compliance with experimental protocol
 - Attrition
- **External validity: Can extrapolate estimates to other populations?**
 - Non-representative sample
 - Non-representative program (treatment differs in actual implementation, scale effects, actual implementations are not randomized)

Observational studies

- **Identification: Selection on observables**
 - there exist observed predetermined variables X , such that the treatment is independent of the potential outcomes conditional on the covariates
 - **predetermined variable:** Variable X is predetermined with respect to treatment if for each i , $X_{0i} = X_{1i}$. i.e., X_i does not depend on the value of D_i
 - justifies the use of estimation methods to control for differences in predetermined characteristics
 - Matching
 - Regression
 - Difference-in-Differences

Observational studies

- Matching estimators: matching on covariates
 - X discrete and takes on a small number of values: $\{X^1, X^2, \dots, X^J\}$
 - n^j : number of observations in cell j
 - n_1^j : number of treated in cell j
 - n_0^j : number of controls in cell j
 - \bar{Y} : average value of Y

$$\hat{\alpha}_{ATE} = \sum_{j=1}^J (\bar{Y}_1^j - \bar{Y}_0^j) \times \frac{n_1^j}{n_1}$$

- when the dimension of X is large, this strategy breaks down: empty cells, hard to find similar covariate values.

Observational studies

- **Matching estimators: propensity score methods**
 - Propensity score: under selection on observables, we call propensity score to the selection probability conditional on the confounding variables
 - Conditioning on the propensity score is enough to have independence between treatment and potential outcomes
 - Two step estimation procedure:
 - Estimate the propensity score, $P(D = 1|X)$
 - Do matching on the propensity score
 - $P(D = 1|X)$ estimated with a probit or logit model
 - Matching average treatment effect on the treated

$$\hat{\alpha}_{ATET} = \frac{1}{n_1} \sum_{i=1}^{n_1} \left(Y_{1i} - \sum_{j=1}^{n_0} w_{(i,j)} Y_{0j} \right)$$

where $w_{(i,j)}$ is the weight of j as a control for unit i

Observational studies

- Regression
 - $E[Y | D, X]$ provides the average potential responses
 - Considering the linear form: $Y = \alpha D + \beta X$

Observational studies

- **Difference-in-Differences**
 - **With pre- and post-treatment data available**
 - Compare outcomes of treated after the treatment with outcomes before the treatment
 - Before-after comparisons are likely to be contaminated: temporal trends and effects of other events on outcome
 - Use untreated comparison group to identify the temporal variation in the outcome not due to treatment exposure

Difference-in-Differences (DinD) is based on this idea

Observational studies

- **Difference-in-Differences**

- Assumption: common trend

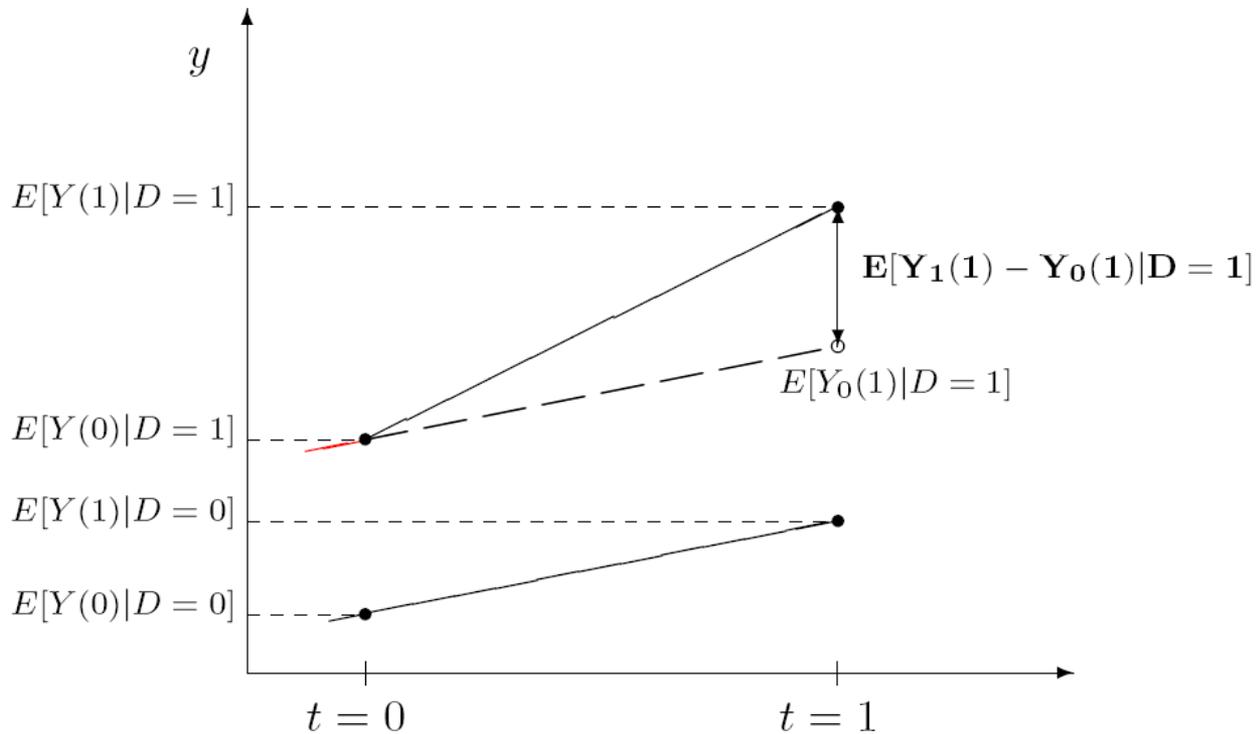
$$E[Y_0(t = 1) - Y_0(t = 0) | D = 1] = E[Y_0(t = 1) - Y_0(t = 0) | D = 0]$$

- If the assumption holds, then

$$E[Y_1(1) - Y_0(1) | D = 1] = \{E[Y(1) | D = 1] - E[Y(1) | D = 0]\} \\ - \{E[Y(0) | D = 1] - E[Y(0) | D = 0]\}$$

Observational studies

- Difference-in-Differences



Observational studies

- **Difference-in-Differences:**

- *ATET* estimate (α)

- For longitudinal data $\Delta Y = \delta + \alpha D + X\beta + u$

- for repeated cross-sections: $Y = \mu + \gamma D + \delta T + \alpha (D \cdot T) + X\beta + \varepsilon$

Observational studies

- **Difference-in-Differences:**
 - **Two threats to the validity of DinD estimators:**
 - **Compositional differences:** The use of repeated cross-sections is only valid when the composition of the target population does not change between the two periods. Can be tested: Distribution of (D, X) must be the same for pre- and post-treatment periods
 - **Non-parallel dynamics:** Sometimes non-parallel dynamics can be controlled for with covariates. However, if dynamic of outcome variable depends on non-observables, identification breaks down. Test parallel dynamics: If there are data for 2 or more periods before treatment, run regression and test $\alpha = 0$