# EE 462 Development Macroeconomics (1/2012)

## Lecture 9- 10 : Human Capital: Economics of Education

# Topics

- Returns to Education or effect of education on earnings
  - Private rate of return
  - Social rate of return
- Relationship between resource allocation and education outcome
- Research topics

# 1. Returns to Education

- ROR as an investment criteria and incentive
- From cost and benefits flows
- Based on human capital earning theory of Jacob Mincer (1974)
- Popular model for many research topics:
  - Returns to schooling
  - Returns to school quality
  - Impact of work experience on male-female wage gaps
  - Relationship between growth and average schooling levels across countries
  - Rising wage inequality in the U.S.

# Mincerian Equation

$$\log y = a + bS + cX + dX^2 + e$$

- Where
- y = earning in a given period (daily/annual/..)
- S = years of completed education
- X = no. of working years : Age – S – 6.
- e = residual
- In practice, S and Age are discrete variables

# 1. Returns to Education

- Underlying hypotheses (a) education is the number of years of completed education; (b) each additional year has the same proportional effect on earnings.
- Thus, b is the return to education or internal rate of return to schooling investment, assuming that education is free and that students earn nothing while in school. (cost of education is only foregone income)
- Adjusted for tuition cost could be made for more accurate calculation
- ? Credentials matter more than years of schooling per se (sheepskin effect). You get wage premiums for fulfilling the final years of high school or college.

# Empirical evidence: world

- The average private ROR to another year of schooling is about 10 % (7-12%).
- Industrial countries : 7 %
- Developing countries : 11 %.
- By education, highest in primary : 27 %
- Secondary : 17 %
- Higher : 19 %
- Source: Psacharapoulos and Patrinos (2004)

# Empirical evidence : Thailand

- Using labor force surveys by NSO.
- Individuals aged from 15 -60, excluding self-employed, part-time workers, and those who work in agricultural sector.
- Y = annual earnings for men and women
- Education attainment as years of schooling or dummy variable
- No report on work experience in paid work.
- Estimation by LS
- Normally will add control variables : area, region, marital status, employment sector, and occupation of person; and some interaction terms between experience and education dummy.
- The average private ROR : 11 -12.9 % (2529-2549)
- By gender, female gets about 0.5 -1.7 % over male.

# Private rate of returns to education: Thailand

**Selected Comparisons of Returns to Schooling Estimates for Thailand**

| Author | Year of data | Method | Return to one additional year of schooling (per cent) | |
|---|---|---|---|---|
| Psacharopoulos (1994) | 1971 | The Coefficient on Years of Schooling | Overall 10.4 | |
| Patrinos (1995) | 1986 | The Coefficient on Years of Schooling | Overall 12.4 | |
| Patrinos (1995) | 1989 | The Coefficient on Years of Schooling | Overall 11.5 | |
| Psacharopoulos (1994) | 1972 | Returns to Education by Level of Education and Gender | Male 9.1 | Female 10.0 |
| This study | 2006 | The Coefficient on Years of Schooling, | Male 11.2 | Female 12.9 |

Source: Psacharopoulos and Patrinos (2002) and authors' (2008) estimate.

Source: Chapman and Lounkaew (2008)

## Years of Schooling Model

| Variable | Female | | Male | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| Schooling | 0.129** | 138.79 | 0.112** | 113.58 |
| Experience | 0.036** | 34.39 | 0.037** | 34.60 |
| $Experience^2/1000$ | -0.1186** | -5.17 | -0.178** | -8.13 |
| Constant | 1.692** | 133.93 | 1.979** | 164.27 |
| n | 17,491 | | 19,856 | |
| $R^2$ | 0.6146 | | 0.5436 | |

*denotes statistical significance at the 5 percent level.
**denotes statistical significance at the 1 percent level.

Source: Chapman and Lounkaew (2008)

# Dummy Variables and Interaction Terms model

| Variable | Female | | Male | |
|---|---|---|---|---|
| | Coefficient | t-stat | Coefficient | t-stat |
| Experience | 0.063** | 32.34 | 0.077** | 47.46 |
| $Experience^2$ | -0.001** | -34.55 | -0.001** | -42.79 |
| Primary | 0.150** | 3.65 | 0.146** | 3.83 |
| Lower Secondary | 0.254** | 7.28 | 0 .221** | 5.49 |
| Upper Secondary | 0.315** | 9.64 | 0.350** | 8.33 |
| Diploma | 0.577** | 11.79 | 0.548** | 9.26 |
| Undergraduate | 0.776** | 28.39 | 0.859** | 19.37 |
| Post Graduate | 1.025** | 15.95 | 1.104** | 11.48 |
| Experience*Primary/100 | -0.019** | -4.12 | -0.018** | -4.34 |
| $Experience^2$*Primary/10000 | 0.006** | 4.92 | 0.007** | 3.58 |
| Experience*LowerSecondary/100 | -0.023** | -4.79 | -0.018** | -4.14 |
| $Experience^2$*LowerSecondary/10000 | 0.810** | 8.31 | 0.734** | 9.14 |

Source: Chapman and Lounkaew (2008)

# Private rate of returns to education: Thailand

- Calculate predicted value of earning by

$$\hat{y} = \exp^{\left(\frac{\sigma^2}{2}\right)} . \exp^{\left(\ln \hat{y}\right)}$$

- Estimated Percentage difference in earning
- Earning increase with education and experience, with the rate of increase with experience falling over time.
- Earning-experience slopes are relatively steeper for graduate as expected.

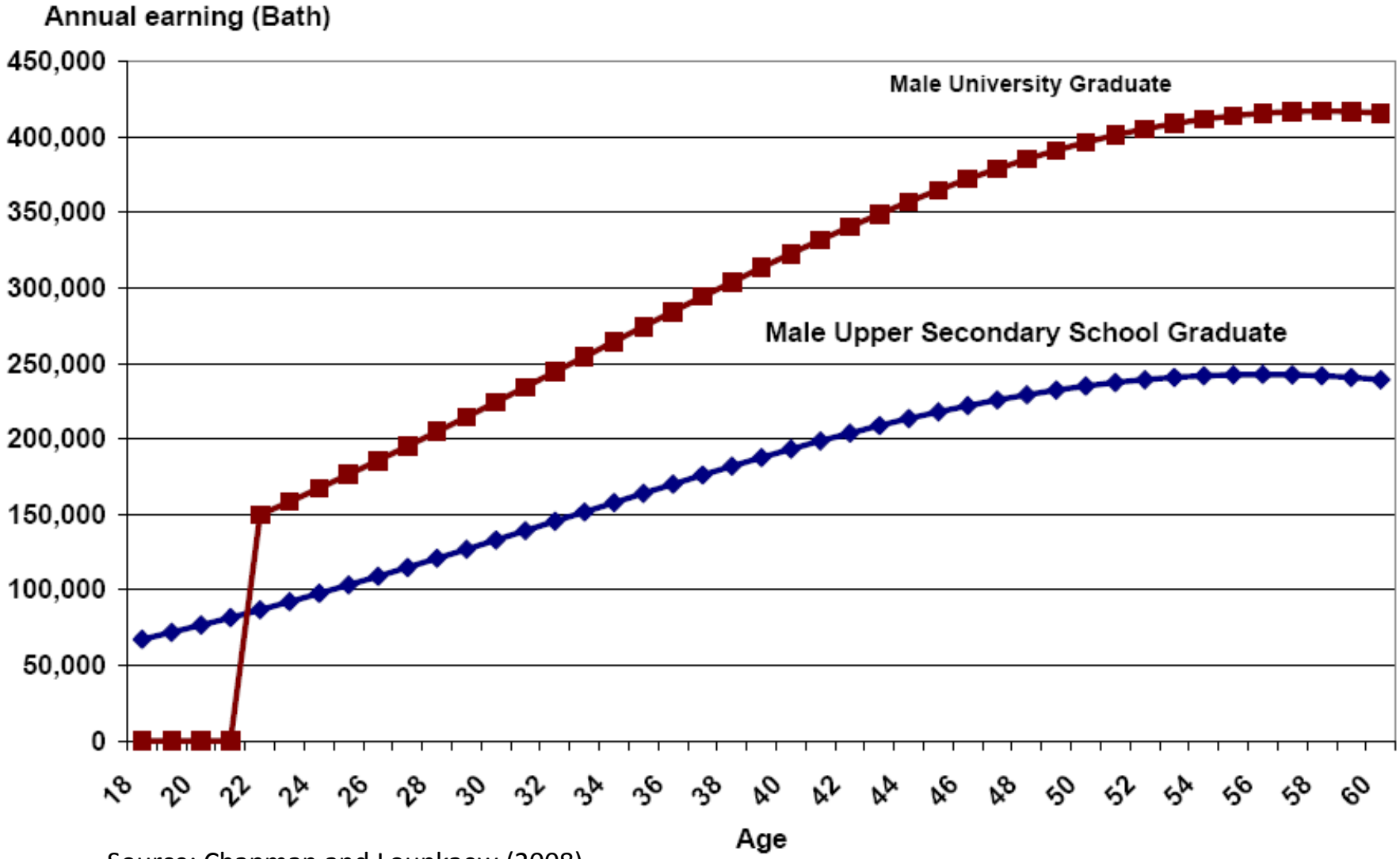
# Percentage differences in earning associated with educational qualifications can be calculated from estimates

**Percentage Differences in Earnings**

| Educational attainment | Male | Female |
|---|---|---|
| Primary | 15 | 14 |
| Lower Secondary | 25 | 22 |
| Upper Secondary | 32 | 35 |
| Diploma | 58 | 55 |
| Undergraduate | 78 | 86 |
| PostGraduate | 102 | 110 |

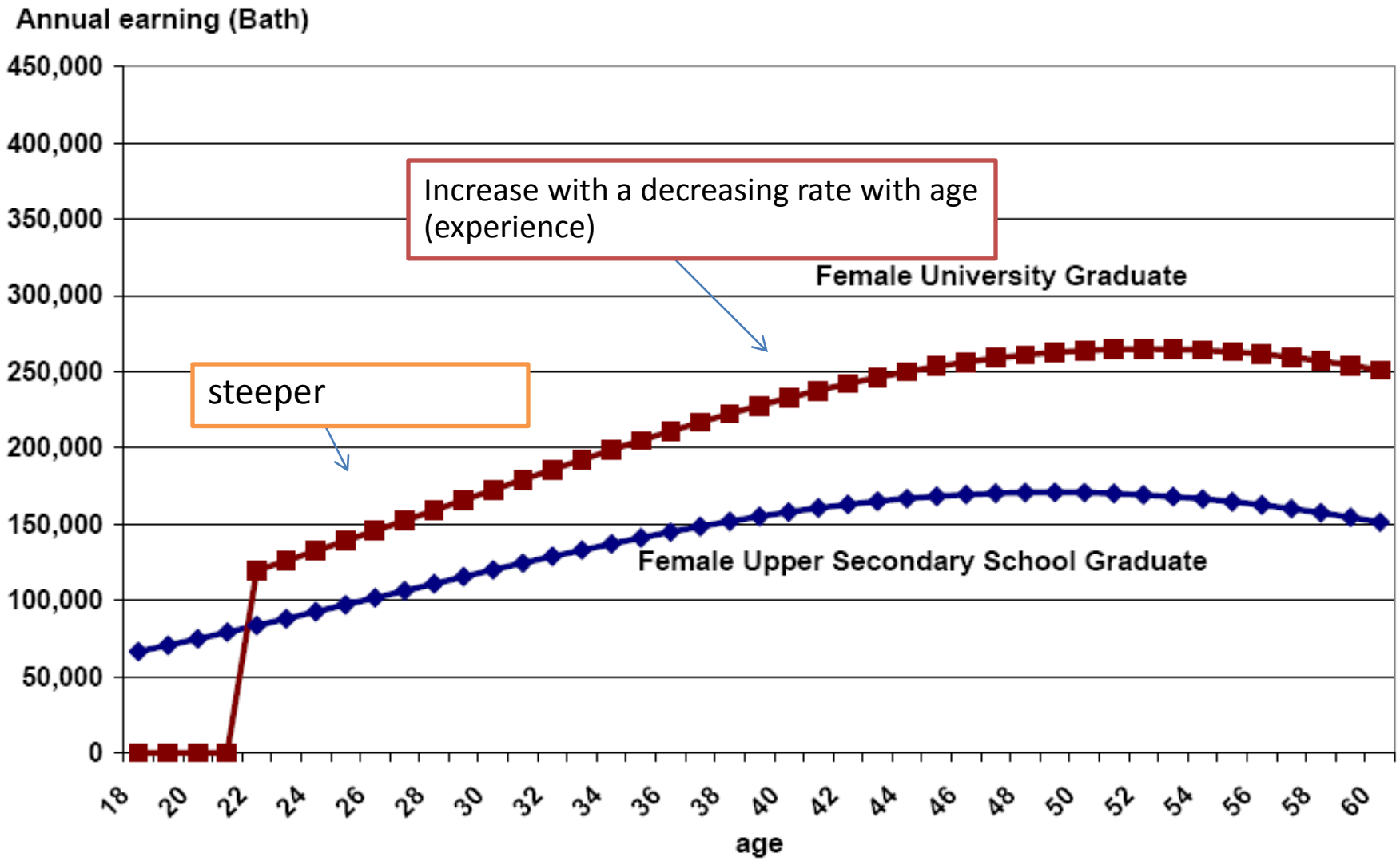
Source: Chapman and Lounkaew (2008)

# Average Male Age-earnings Profiles (Thailand, 2006)




Source: Chapman and Lounkaew (2008)

# Average Female Age-earnings Profiles (Thailand, 2006)




Source: Chapman and Lounkaew (2008)

# Calculation of IRR

We can use these results to calculate the so-called internal rate of return to investment in university education, a measure of the value in earnings terms of process. Formally, the IRR is defined as the discount rate that equates the present value of additional benefits from the investment to the present value of the cost of obtaining the additional education. The benefits are additional earnings from higher education; and the costs are tuition fees plus the opportunity cost of not working in paid employment after the completion of upper secondary school. It should be noted that the result from the IRR estimate is contingent upon both the cost of investment and the earnings streams.

In our estimates we assume that university graduates undertake study on a full-time basis for four years and receive zero incomes at that time. The calculations have been carried out for a diversity of tuition fees, from 36,000 Baht to 350,000 Baht per program, which reflect very broadly the current range of Thai higher education annual tuition charges for different institutions. Table 5 shows the results with the IRRs, and these range from 8.0 to 12.8 per cent per annum for males, and 4.5 to 7.9 per cent per annum for females, estimates which are roughly in line with international experience (see Psacharopoulos and Patrinos, 2002). This familiarity should leave us with some confidence that the data and the methods employed are useful for describing the Thai graduate experience

Source: Chapman and Lounkaew (2008)

# Calculation of IRR: from average age-earning profiles

**IRR Estimates (per cent per annum)**

| Tuition prices by type of institution* | | Total Tuition Fee (Baht)* | Male | Female |
|---|---|---|---|---|
| Public University | Low price | 36,000 | 12.79 | 7.93 |
| | High price | 144,000 | 10.41 | 7.13 |
| Private University | Low price | 192,000 | 9.23 | 5.55 |
| | High price | 350,000 | 8.04 | 4.48 |

* Average estimates from various universities.

Source: Chapman and Lounkaew (2008)

# Calculation in practice

$$starting\ with\ earning\ from\ two\ persons\ having\ edu\ A\ and\ B:$$

$$\frac{y_A}{y_B} - 1 = \frac{e^{a+b_A S_A + \ldots}}{e^{a+b_B S_B + \ldots}} - 1$$

$$= \frac{e^{b_A S_A}}{e^{b_B S_B}} - 1 \quad [holding\ other\ characteristics\ equal\ except]$$

$$= \frac{e^{b_A S_A}}{e^{b_B S_B}} - 1 = e^{b_A - b_B} - 1.$$

$$If\ we\ drop\ one\ dummy\ of\ education\ level\ from\ the\ regression,$$

$$, say, primary\ as\ base\ \text{int}ercept. Thus, b_B = 0. Hence,\ we\ get$$

$$\frac{y_A}{y_B} - 1 = e^{b_A} - 1.\ This\ shows\ an\ increase\ in\ earning\ as\ a\ result\ of$$

$$prolonging\ from\ primary\ up\ to\ level\ B\ of\ education.$$

$$\text{Pr}ivate\ ROR = (e^{b_A} - 1) / (no.of\ years\ between\ primary\ and\ B)$$

# Calculation in practice

- Sometimes, we can use approximation by

$$e^{\beta} \approx 1 + \beta, \; or$$

$$e^{\beta} - 1 = \beta.$$

$$We\ can\ use\ LS\ estimates\ from\ Mincerian\ regression\ to\ calculate\ the\ private\ rate\ of\ returns.$$

# Econometric issues

- Potential bias in estimated returns caused by unobserved variables that may both affect earning and be correlated with x, such as ability, family background.
- Recent evidence from natural experiments or IV methods suggest that omitted ability does not cause upward bias in the returns (Card 1999, HB of Labor Economics; Krueger and Lindahl 2001, JEL)
- Griliches (1977, Econometrica) finds that upward ability bias is about the same order of magnitude as the downward bias caused by measurement error in educational attainment.

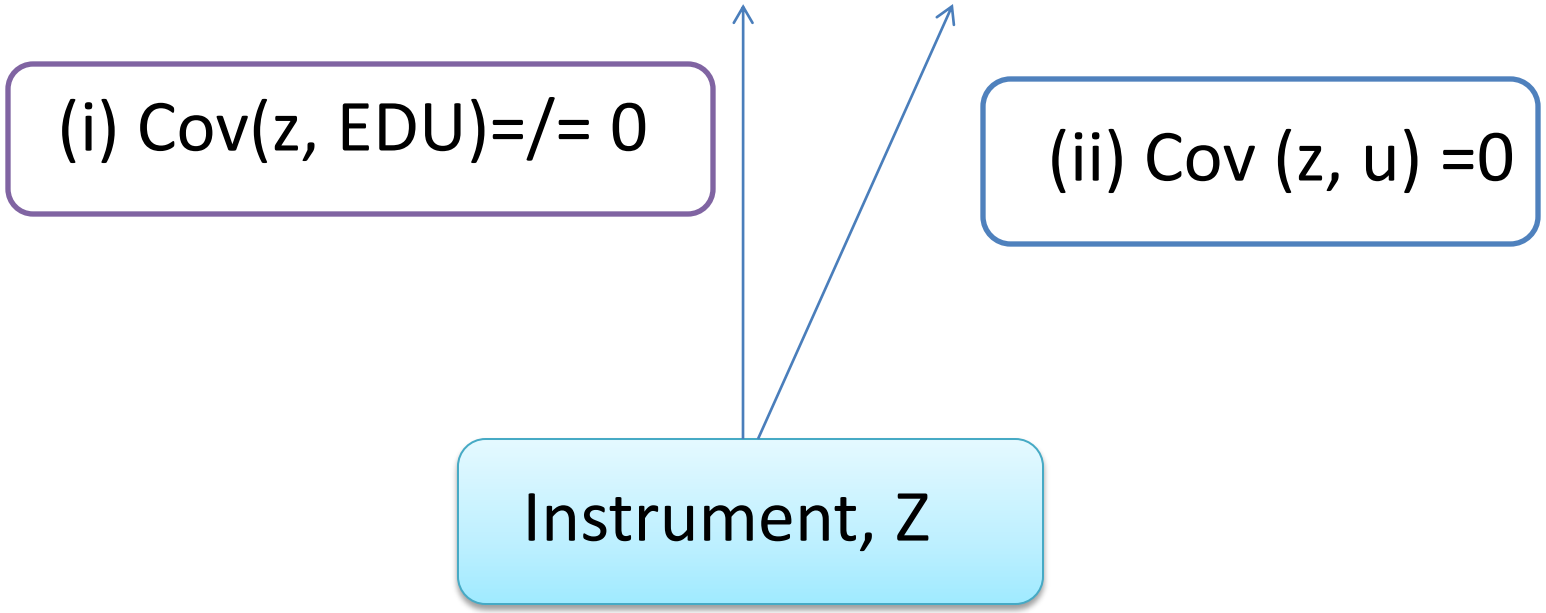
# Econometric issues

- Simple solution is to find a good proxy for ability. We want this proxy to be correlated with the unobserved variable (*).
- Suppose we cannot find a good proxy for unobserved ability. Possible solution are
- (a) ignore it and suffer from bias in using OLS.
- (b) use fixed effect model
- (c) use instrumental variable method

# Econometric issues:

## Instrumental Variable method

- Log(wage) = bo + b1*EDU + u



# Instrumental Variable method

- How do we find Z? Two conditions are needed
- (i) Correlation between Z and EDU can be tested by regress EDU on Z.
- (ii) Z must not be correlated with ability and also other unobserved factors affecting wage (hiding in u)
- Remarks. (b) requires just opposite to a good proxy (*)

# Instrumental Variable method

- In short, we can try to control for family background; or
- Instrumental Variable method:
  - use institutional feature of school system as the source of identifying information for separating the causal effects of schooling.
  - use family background as an instrument for schooling. For example, use mother's education (correlate with child's education (i), but may violate (ii) since it relates to child's ability). Another example, use number of siblings: (i) negative relate with child's education, and (ii) it is not related with ability of that child.

# Instrumental Variable method

- Test scores = bo + b1*(no. of absence) + u
- Want to know b1, but we know there is some unobserved variable, say ability, hiding u. Smart kid does not skip school often. Thus, u and x is correlated, and LS is inconsistent.
- Need to find an instrument Z: (i) relate with numbers of absence and (ii) not related with ability.
- Good IV is distance from school. We can hypothesize that longer distance from school leads to more missing class (testable).
- Does this instrument satisfy (ii)? What if distance relates with parent's wealth which might cause score, thus hiding in u also. If so, distance will relate with u (via income of parents)

# Econometric issues

- Natural experiment or randomized experiment approach is to make sure that variability in schooling generated by the natural experiments is unrelated to individual earning.
- One wants to randomly assign individuals to different levels of education. We look for events or situations that treat identical persons very differently and that affects their education decisions only but not their later earnings. (this creates IV variable for regression)
- Angrist and Krueger (1991, QJE) use the quarter of birth to assign the level of education. Later works uses proximity to college, or changes in compulsory school laws as an instrument for schooling.
- Mostly, these groups of works found returns to education are at least as high as the returns obtained with OLS.

# Econometric issues

- But if we begin with the belief that LS lead to upward-biased estimates of the true return, then the larger IV estimates present something of puzzle.
- Explanations: (a) IV can be even more upward-biased than LS by unobserved differences between characteristics of treatment and control group in the IV scheme (given no control for family background).
- (b) Ability biases in LS are quite small. Also LS is downward bias due to measurement error.
- (c) picking bias by researcher: choose specification that yields a larger estimate
- (d) there are underlying heterogeneity in the returns to education. Using IV based on institutional changes may overstate schooling level among less-educated subgroup of population.

# Econometric issues

- Another is to clone individuals so that identical twin can attend different levels of education.
- This assumes that identical twins share the same genetic and social characteristics so that there will be no systematic difference in their earnings if getting the same education level.
- So, if they require different levels of education, any observed earning difference can be attributed to this educational difference.
- Results are also not different from OLS.

# Econometric issues

- Future issues:
  - heterogeneity of returns across wage distribution
  - IRR of graduates across earning distribution (interest subsidies policy): quantile regression or truncated OLS
  - returns for more disadvantaged individuals are higher,
  - Returns for pre-school education or early childhood investment

# 2. Social Rate of Return

- Policy makers consider social rate of return, how much to invest in education, and who bare the cost.
- Social benefits of education include
  - Private benefits (both market and non-market) smart purchase, good health
  - Externalities; lower crime rate, higher average group productivity, democracy

# 2. Social Rate of Return

- Rationale of government intervention: market failure, lower that socially optimum level of investment
- How large is the social rate of return?
- If SROR > PROR, this means the society needs more education investment that other types of public investment eg. Infrastructure.

# 2. Social Rate of Return

- Role of education in explaining economic growth
- (1) rate of human capital accumulation affects long-run growth rate (Lucas 1988).
- (2) Stock of human capital affects growth rate (Romer 1990) (Nelson and Phelps 1966 technology adoption)

# Macro-Mincerian

- Next, if we assume that Human capital is built through schooling as follows:

  $h_i = \exp\{rS_i\}$ ; $\ln(h_i) = r\, S_i$

  where r is the return to education and S is educational attainment or average years of schooling of country i.
- We get the Macro Mincerian equation in which r is to be estimated and also interpreted as “the social rate of return”.
- Under the absence of human capital externalities, r should be close to the private rate of return.

# Macro-Mincerian

- Shorter-form of Macro-Mincer wage equation by Heckman et al. (2003 NBER):
- $\ln y^g = b0 + b1 * S + e$ (drop subscript jt)
- $Y^g$ is geometric mean wage
- S is mean education
- Control for country difference
- Sometime, we take first difference
- Found that change in education is positively related with growth once measurement error in education is accounted for, thus contrasting with Benhabib and Spiegel (1994, JME) and Barro and Sala-i-Martin (1995, book)

# 2. Social Rate of Return

- The next model treats human capital as public goods. Thus, average human capital in one state can affect labor productivity in that state.
- Acemoglu and Angrist (2001, NBER) estimates log wages on years of schooling and state average years of schooling and some controls, using U.S. individual data. Use IV for state average education and for individual education. They find the private ROR is about 7 % and the external return is small and statistically insignificant.

# 2. Social Rate of Return

- Moretti (2004, JoE) estimates the relationship between individual wages and the fraction of individuals with college degrees in U.S. cities.
- Using manufacturing census and pop census
- Deal with endogeneity by using city dummies and IV for average education by lagged age structure in the city.
- Estimated externalities of the size 17 %

# Estimating social rate of return

- Evidence suggests both rates are of the same size, suggesting no substantial human capital externalities (Lindahl and Canton 2007).
- Thus, based on both approaches, we tend to conclude that there is no substantial human capital externalities.. (Lucas failed)

# Other issues

- Education and crime: educated person will commit less crime. Using IV to measure schooling, Lochner and Moretti (2004 AER) find that schooling significantly reduces prob. Of incarceration.
- Knowing cost saving from crime reduction and cost of high school graduation, they estimate savings of 2000 USD per additional high-school graduate, or 26 % of private return.

# Other issues

- Education and health: higher level of education may result in better health of his own and his children.
- This suggests important intergenerational spillovers that wage effects will not capture.
- Currie and Moretti (2003 QJE) examine the effect of maternal education on birth outcomes for children in the U.S. (via better prenatal care, less smoking, in marriage, and less fertility). IV for maternal education (subject of interest). They find positive effects.

# Other issues

- Education and Voting. A more educated voter enhances the quality of the democratic process, since they make better decisions on policy issues affecting the economy.
- Milligan et al. (2004, JPE) test whether schooling improves civic participation (probably of voting) in U.S. and U.K. They found positive strong effects in the U.S.

# Readings

- David Card (1999). “The Causal Effect of Education on Earnings,” Handbook of Labor Economics, volume 3.
- Krueger A.B. and M. Lindahl (2001), “Education for Growth: why and for whom?, Journal of Economic Literature.
- List, J. and I. Rasul (2010), “Field experiments in Labor Economics,” NBER.
- Glewwe, P. (2002), “Schools and Skills in Developing Countries: Education Policies and Socioeconomic Outcomes,” JEL.

# 2. Relationship between resource allocation and education outcome

- View school as location where education is produced using inputs.
- Literature focusing on studies of inputs used in the educational production function.
- These inputs might be supplied by the school system, students, or their families.
- Following Glewwe and Kremer's (2006, HB of economics of education)

# 2. Relationship between resource allocation and education outcome

- A reduced form representation of the education production function

$$S = f(C, H, Q, P) \quad \ldots(1)$$

$$A = h(C, H, Q, P) \quad \ldots(2)$$

- Where S is years of schooling, A is skilled learned (achievement), C is a vector of child characteristics (including innate ability), H is a vector of Household characteristics, Q is a vector of school and teacher characteristics (quality), and P is a vector of prices related to schooling.

# 2. Relationship between resource allocation and education outcome

- Since Q and P are both functions of education policies (EP) and local community characteristics (L), we can substitute into (1) and (2) as

$$S = f(C, H, L, EP) \quad \ldots(3)$$

$$A = h(C, H, L, EP) \quad \ldots(4)$$

- Partial equilibrium effect v.s. general equilibrium, in which affects the returns to education and thereby demand.

# 2. Relationship between resource allocation and education outcome

- Two approaches to estimating the production function.
- First, focusing on measuring the effect of direct input, such as per pupil expenditure, class size, teacher quality, and family background. = estimating eqs. (1) and (2).
- Second, examining the effects of educational policies governing the structure of the school system such as vouchers (demand-side financing), decentralized adminitration of public schools, or promotion of private schools. = estimating eqs. (3) and (4).

# 2.1 Measuring effects of direct inputs

- Early studies found only a weak association between school inputs and outputs through simple regression.
- Output =f (inputs) .
- Output= schooling and achievement (or sometimes called student performance or learning outcome ).
- Example. Output = Standardized test scores (in cognitive skills), school completion rate, drop out rate or earning in the labor market.
- Inputs = individual characteristics, family background, and parental resources, teacher quality.

# 2.1 Measuring effects of direct inputs

- Proxies for School inputs = pupil-teacher ratio, per-pupil expenditures, school size, type of school (note that these are generally measured at the school or district level).
- Knowing which specific school characteristics have great impact on learning is ideal. If so, knowing too cost data on these characteristics, we can calculate the cost effectiveness of such characteristic. (output per dollar spent)
- Note that the production function approach cannot answer how hh may response to policies. For example, if school quality increases, parents may reduce their time spent helping their children with homeworks.

# 2.1 Measuring effects of direct inputs

- Hanushek (1997)'s survey for the US studies lead to conclude that it is not clear if greater school resources will have a positive effects on pupil's learning outcome.
- Also found that there were large differences in such relationship and in estimates of resource effect parameters, suggesting inefficiency in the system.
- Criticized by Krueger (1999, QJE) that putting equal different weight to each publication may yield a larger proportion of significant results.

# 2.1 Measuring effects of direct inputs

- Econometrics problems
- 1. reverse causality (endogeneity of school inputs )
- 2. omitted variables bias (unobserved heterogeneity)
- 3. measurement error (unobserved teacher quality)
- 4. others (functional forms, aggregation bias)
- Leading to biased results

# 2.1 Measuring effects of direct inputs

- Consider the two-equation structural model

$$y1 = a1\ y2 + b1\ z1 + u1$$

$$y2 = a2\ y1 + b2\ z2 + u2$$

we can writhe the reduced form

$$y1 = c1\ z1 + c2\ z2 + v1$$

$$y2 = d1\ z1 + d2\ z2 + v2$$

Regress the structural model suffers from simultaneity bias. OLS is biased and inconsistent.

# 2.1 Measuring effects of direct inputs

- 1. Endogeneity of school inputs
- Resources allocated to the education process may not be exogenous to the student outcome or performance.
- Amount of resources depends on choices by politicians, administrators, teachers, parents, which may be based on level of performance.

# 2.1 Measuring effects of direct inputs

- 1. Endogeneity of school inputs
- For example. Rich parents select good school quality. Thus, school quality is positively correlated with the economic and social advantages of children families.

# 2.1 Measuring effects of direct inputs

- 1. Endogeneity of school inputs
- Generally, the direction of bias caused by endogeneity is ambiguous (Hoxby 2000).
- For example, if poor performance leads to an increase in available resources, this will lead to estimates of resource effect to be biased downwards.
- Another example, when class size is a choice variable in which administrator manages to have a larger class with less resources to better students. Thus, we found more resource with less performance in regression.
- Or if gov. gives more per-head expenditures to weaker students, this will also bias the estimated resource effect downwards.

# 2.1 Measuring effects of direct inputs

- 1. Endogeneity of school inputs
- In opposite, if better students get more, this will cause an upward bias for resource effects.
- Between-school resource variations could also lead to the similar bias.
- Endowing better students with special facilities to support elite students. (public university, Mahidol schools)

# 2.1 Measuring effects of direct inputs

- To solve this problem, we offer some solutions

  (a) value-added models
- It uses a change in student's test scores as a dependent variable. Then, it includes the student initial test results as additional explanatory variable.
- Obviously, innate ability and attainment prior attending school are important as they reflect the fact that some children are more able than others, already had better schooling, or receiving greater parental supports.

# 2.1 Measuring effects of direct inputs

(b) instrumental variables (IV)

- to find an instrument(s) for the endogeneity variable (rather than specifying the full simultaneous equation model).
- For LS, endogeneity cause the X variable to be correlated with the error term (not independent)
- Good IV is hard to find.
- Need one to relate to school inputs but not directly influencing learning outcomes.

# 2.1 Measuring effects of direct inputs

(b) instrumental variables (IV)

- Example . We want to identify effect of class size on outcome. Use random birth rate and legal limits to class size to identify random variation in class size. (so that variation of class size not come from variation of children characteristics in the class)

# 2.1 Measuring effects of direct inputs

- (C) Randomized experiments
- Compare two groups of observations : treatment and non-treatment (control) groups. If these 2 groups are randomly divided. Differences in x across 2 groups are unbiased estimates of the effect of treatment.
- Useful for program evaluation

# 2.1 Measuring effects of direct inputs

(C) Randomized experiments

- use experimental data.
- Costly since must be implemented at the class room or school level (not at individual level as in medical science).
- Moral problems (cannot play with human)
- Results in education may be locally specific to culture or school system (cannot apply generally anywhere)
- When being a subject of study, you will change your behavior (Hawthorne effects)

# 2.1 Measuring effects of direct inputs

- (C) Randomized experiments
- Tennesse STAR experiment to test the effects of classroom size. Students were randomly assigned to classes of different sizes from K to G-3.
- Still, attrition bias and selection problems.
- They found achievement gains from studying in smaller classes.
- Overall, mixed evidence on the effect of class size at various tiers of the education system.
- Thought: threhold effect: If too small, lost peer effects. What about the composition of classrooms or peer composition?

# 2.1 Measuring effects of direct inputs

- (C) Randomized experiments
- Examine a wide range of targeted investments to identify effects and compare the cost-effectiveness of various interventions.
- For example, school supplies, additional teachers, remedial education, or computer-aid programs.
- Banerjee et al. (2007, QJE) focus on learning of weaker students. They claim that neither more inputs nor an extra day in school makes much of a difference for them (too difficult, cannot read textbook in English). Thus, inputs specifically targeted to helping weaker student learn may be effective.

# 2.1 Measuring effects of direct inputs

- (d) natural experiments
- Find natural variation in school characteristic that is uncorrelated with anything that affect learning.
- Angrist and Lavy (1999, QJE) use legal rules to estimate the effect of class size on student performance. Assume legal limits on class size prevent no.of students in a classroom from exceeding 25. Then look at a particular school that has cohorts ranging from 70-100. (100=>4 classroms@25, 76=>4classrooms@19)
- Still, good schools attract more students, thus cohort sizes might not be randomly determined.

# 2.1 Measuring effects of direct inputs

- 2. Omitted variables bias or unobserved heterogeneity
- lacking a theoretical model of how school resources may impact on educational outcomes.
- Ex. It may argue that learning “process” and inputs are equally important. Or peer effects and community environment are as important as school environment.

# 2.1 Measuring effects of direct inputs

- There are some unobserved elements of the vectors of inputs which will be correlated with both the outcome and other observed variables of interest.
- OLS is generally inconsistent and biased.
- Easiest Solution is to find a proxy variable for the unobserved variable. Or if such omitted variable does not change over time we can use the fixed effect (first differencing) method.
- Another solution is to leave it in the error term and look for the instrument z such that cov(z, e) =0 and cov(z, x) =/= 0.

# 2.1 Measuring effects of direct inputs

- Ex. Log(wage)= bo+ b1 edu + b2 abil + e
- 1. use IQ as a proxy for abil, thus run

  Log(wage)= bo+ b1 edu + b2 IQ + e
- 2. use IV, say no. of siblings, thus run

  Log(wage)= bo+ b1 No.sibl + e

  More No. of siblings implies less average education, but uncorrelated with ability.

Other candidate IV maybe FatherEducation

# 2.1 Measuring effects of direct inputs

- Ex. Log(wage) =b0 +b1edu +b2exp + e
- Using IV, look for z to replace edu, where cov(z, e ) =0 and also edu and z are still correlated after partialling out experience.

# 2.1 Measuring effects of direct inputs

- 3. unobserved teacher quality
- Improving teaching quality or child ability that can improve achievement.
- Evidence on the effect of per-pupil expenditure, class size, and peer composition is mixed.
- However, teacher quality has been found to be clearly important.
- Hanushek (2007, Schools and the equal Opportunity Problem, MIT Press) finds that the differences between schools can be attributed to teacher quality difference.

# 2.1 Measuring effects of direct inputs

- Little variation of school differences can be explained by either teacher salaries or teacher education and experience.
- How to improve teacher quality and performance is a much bigger problem.
- Educational and professional development are largely ineffective.
- Growing interest to use performance-based incentives for teachers. ( for Thailand !!!)
- Evidence shows incentives can improve teacher performance (Duflo et al. 2009, NBER)
- Thought: how to design incentive schemes and cost effective? How teacher sort into different incentive scheme (พนักงานของรัฐ ข้าราชการ) ? How does sorting affect overall teacher quality?

# 2.1 Measuring effects of direct inputs

- 4. Forget our teacher, think about our baby.
- Along with school inputs, the primary inputs come from student and their families.
- Instead, try to model effects of individual characteristics, family background and parental resources on achievement (Cameron and Heckman 2001, JPE).
- Or focus on potential barriers to individual investment in human capital production. For example, high cost of education (due to credit constraint or high discount rate), low marginal returns to education due to poor health or low-endowed prior entering school.
- Many studies found cash-transfer or student loans are helpful.

# 2.1 Measuring effects of direct inputs

- Another strand of Intervention focuses on investments on early childhood.
- Yielding long-run better returns on educational achievement, attainment, and other outcomes (employment, crime, fertility and health) See Heckman et al. (2010, JPubE)
- The last strand of literature focuses on improving child health as a means of increasing school attendance rates.
- This area shows that health interventions have a positive and significant effect. Also, it needs to take into account externalities of health program.
- Ex. Deworming children.

# 2.2 Measuring the effects of policies Governing the system.

- Failure of  input-based approach
- Examining the effects of school competition, school choice, school vouchers, school accountability, and the presence of charter schools.
- Arguing that choice and competition will improve overall school quality and efficiency.
- Still found mixed evidence on these policies.

# Readings


- Vignoles, A. et al. (2000). The relationship between resource allocation and pupil attainment: A review. Centre for the Economics of Education.
- Burtless, G. (ed. )(1996). Does Money Matter: The effect of school Resources on Student Achievement and Adult Success. Brooking Institute Press, Washington, D. C.
- Heckman, J. and A. Krueger (2003). Inequality in America: What role for Human capital Policies. MIT press.

# Measuring Human Capital

- The improved measure of aggregate human capital has many potential uses.
- First, the better estimates of human capital may have an important caveat for economic analysis of its role to economic performance. The obvious example is its use in growth accounting, a method to assess the role of capital accumulation and technological changes (Solow residuals). Moreover, it allows policy makers to more fully understand the role of human capital to economic development.
- Second, rapid changes in demographic factor could affect the quality of its labor force. With a suitable measure of human capital per worker, we can estimate more accurately the changing pattern of the effective labor force.
- Third, a proper measure of human capital will be useful in testing the competing models. A better and more precise estimate of human capital will yield different parameters in economic models, possibly implying different policy implications.

# Measuring Human Capital

- *Adult Literacy Rates*
- Literacy can be defined as the people ability to read and write a simple sentence with understanding.
- Adult literacy rate measures the proportion of adult who are literate of to total population.

$$l = Lr / PA$$

- where *l* is the adult literacy rate, *Lr* is the number of literates in the adult population, and *PA* is the total adult population.

# Measuring Human Capital

- This proxy obviously reflects a component of the relevant stock of human capital. Adult literacy only grasps the first stage of human capital accumulation (writing, reading, and arithmetic). However, it ignores most of the investments made in human capital over lifetime. Any investment beyond the acquisition of basic literacy is neglected in this measure. Using such a measure assuming that knowledge and skills acquired beyond basic levels do not contribute significance to productivity. Hence, adult literacy rates underestimate the total stock of human capital.
- Although many drawbacks, this proxy was used in many studies of cross-country growth regressions (Romer1990, Azariadis and Drazen 1990). Since the data set of adult literacy published by UNESCO and the World Bank, and the data for a large number of countries compiled by Summers and Heston (1988, 1991) are available, it was used as a proxy for human capital in many cross-countries analyses.

# Measuring Human Capital

- *School enrolment ratios*
- School enrolment ratios is normally defined as the number of students enrolled at a grade level relative the corresponding school-age group.
- These enrollment ratio have been used to proxy for human capital in many studies (Barro 1991; Mankiw et al 1992; Levine and Renelt 1992). But as pointed out by Gemmell (1996), the enrollment rate is not suitable for the proxy of human capital because it cannot distinguish between stock and flow.

# Measuring Human Capital

## Average years of schooling

The average years of schooling is another popular method for measuring human capital. This method implicitly assumes that productivity is linearly related to numbers of schooling years. Workers with higher years in schools are more productive and able to learn from work experience. Thus, human capital can be measured as

$$H = \sum_{s} \phi_s \rho_s L \qquad (1)$$

where subscript $s$ represent the level of schooling; $\rho_s$ is the share of worker with $s$ year of schooling [$\rho_s = L_s / L.$]; and $\phi_s$ is the weighted parameter for $s$ level of schooling. In (1), each type of worker contributes to human capital according to his productivity $(\phi)$. Under this approach, the weighting parameter is the year of schooling at each level of schooling.

This method is popular for its ease in calculation. However, some drawbacks are noted. Importantly, this method assumes that differences in worker productivity is proportional to differences in numbers of schooling. In other words, one extra year in school is assumed to increase worker productivity at the constant rate. Thus, this cannot take into account changes in school quality over times.

# Measuring Human Capital

- *Income-based approach*
- To correct the drawbacks discussed above, the income-based approach uses the remuneration of the worker in the labor market rather than the years of education as weighing terms in (1). Human capital can be measured by

$$H = \sum_s \psi_s \rho_s L \qquad (2)$$

- where is the earning from the worker with s year of schooling. The weighting parameters for each level of education are thus the efficiency parameters for each educational level, and needs to be estimated.
- This approach assumes that productivity increases non-proportionately with years of education. Workers with different educational levels are not assumed to be perfectly substitutes.

# Measuring Human Capital: Thailand

As discussed earlier, the more appropriate way is to allow for the fact that workers with different productivity receive different earning. Thus, the weighting parameter to aggregate the human capital from different levels of educational attainment should reflect differences in productivity. It is well known in labor economics that wages or productivity depends on both years of educational attainment and experiences. Thus, we can measure human capital by

$$H = \sum_{s} \sum_{x} \psi_{s,x} \rho_{s,x} L. \tag{3}$$

The weighting parameter can be defined as

$$\psi_{s,x} = e^{\gamma s + \eta x + \mu x^2} \tag{4}$$

where $s$ is year of schooling, $x$ is years of experiences, and $\eta$, $\mu$, $\gamma$ are parameters to be estimated. To estimates these parameters, we employ the popular Mincerian earning equation.

Table 4. Estimation Results of the Mincerian Equation

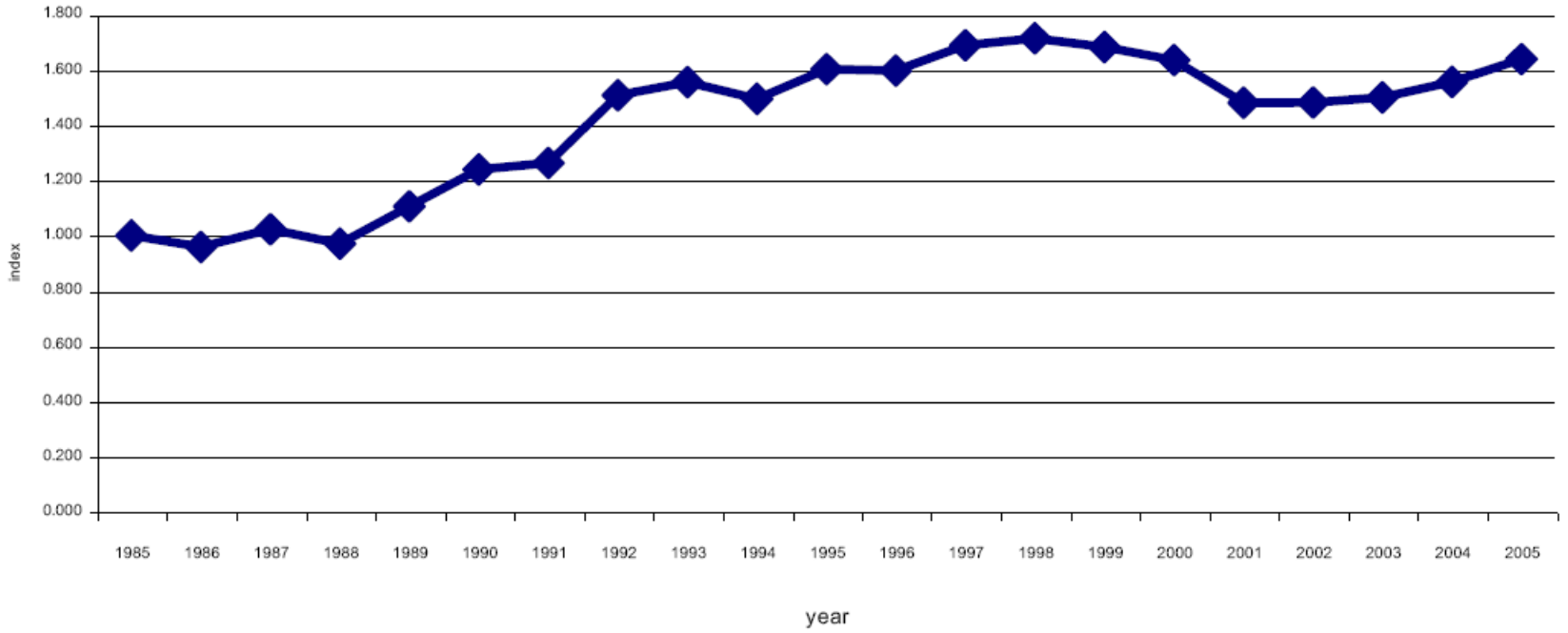
| Year | education | experience | experience squared | R-squared | No. of Obs. |
|---|---|---|---|---|---|
| 1985 | 0.111 | 0.075 | -0.001 | 0.42 | 2717 |
| | (0.005) | (0.010) | (0.000) | | |
| 1995 | 0.103 | 0.017 | - | 0.45 | 7,655 |
| | (0.008) | (0.013) | | | |
| 1998 | 0.103 | 0.027 | - | 0.47 | 6493 |
| | (0.004) | (0.007) | | | |
| 2001 | 0.12 | 0.05 | -0.0007 | 0.44 | 45,873 |
| | (0.0006) | (0.0009) | (0.00002) | | |
| 2005 | 0.119 | 0.055 | -0.0007 | 0.5422 | 204,679 |
| | (0.0003) | (0.0004) | (0.000007) | | |

Source: Author's calculation from the Labor Force Survey data.

Note: - Dependent variable is log of annual earning.

- Estimates for 1985, 1995, and 1998 come form Hawley (2004) p. 279 for Thai men samples.

# Thailand Human Capital Index 1985-2005 Using Relative Earning from Mincerian Estimation As Weighting Terms

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