Piece Rates - Evidence

Class 4 - July 15, 2010

Pre-requisite: Appendix B
Readings: Shearer (Sections 2-4, except 4.1)

Introduction

- When effort cannot be observed, piece rate contracts provide better incentives than salary contracts.
  - Piece rate workers should be more productive than salary workers, all else equal.

- Is this prediction true in the real world?
  - Productivity depends on many factors; e.g. experience
  - How can we tell if how workers are paid has an independent impact on productivity?

Outline

1. Case Study: Planting Trees in B.C.
2. Incentive and Selection Effects of Piece Rates
3. Rubin Causal Model
4. Empirical Strategy: Randomized Experiments
5. Application: Shearer (2002)

1. Case Study: Planting Trees in B.C.

- The Ministry of Forests awards contracts to firms through a competitive auction to reforest recently logged tracts of lands
- The firms employ workers to plant trees
- The tree planting job:
  - Dig a hole in the ground with a shovel
  - Place the seedling in the ground
  - Fill the hole in
- **How to pay workers?**
  - Hourly rate (i.e. salary)
  - Fixed amount per tree planted (i.e. piece rate)

2. Incentive and Selection Effects

- All else equal, piece rate workers should be more productive than salary workers.

Example

- Suppose $q=e+u$, with $E[u]=0$
- Piece rate workers: $E[q]=e^*>0$
- Salary workers: $E[q]=0$

Self-Selection

- What if workers differ in ability, experience, etc.?
- E.g. suppose that q=e+u+n, where n is ability
- Where should worker of ability n work?

Piece Rate Firm

- The expected utility is E[w]-c(e*)=a*+e*+n-c(e*)

Salary Firm

- The expected utility is S-c(e)=R-c(0)=R

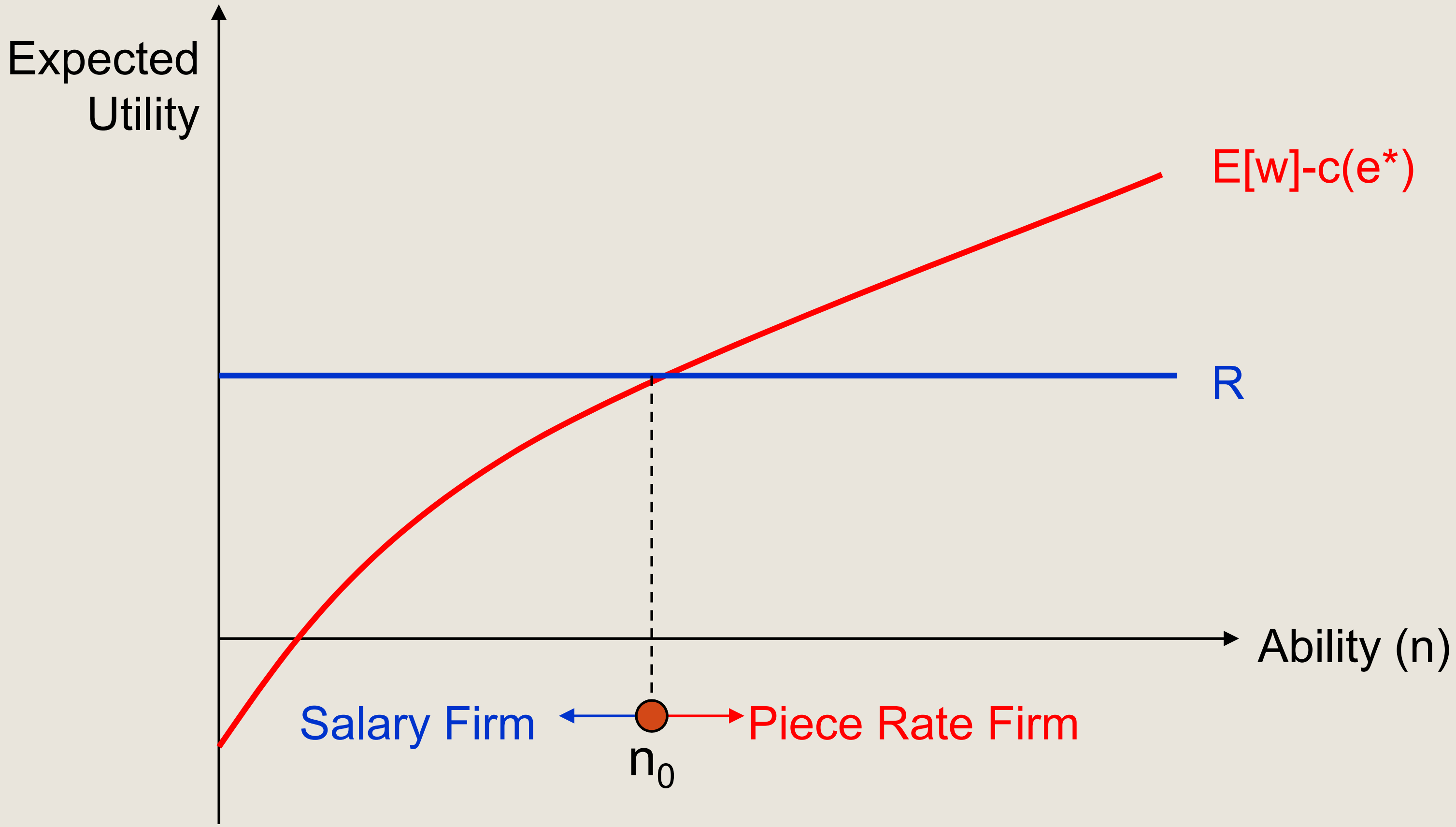
Optimal Choice

- A worker will prefer to work for piece rate firm if

$$a^*+e^*+n-c(e^*)>R$$

$\Rightarrow$ **More able workers more likely to work for piece rate firms**

2. Incentive and Selection Effects



Example

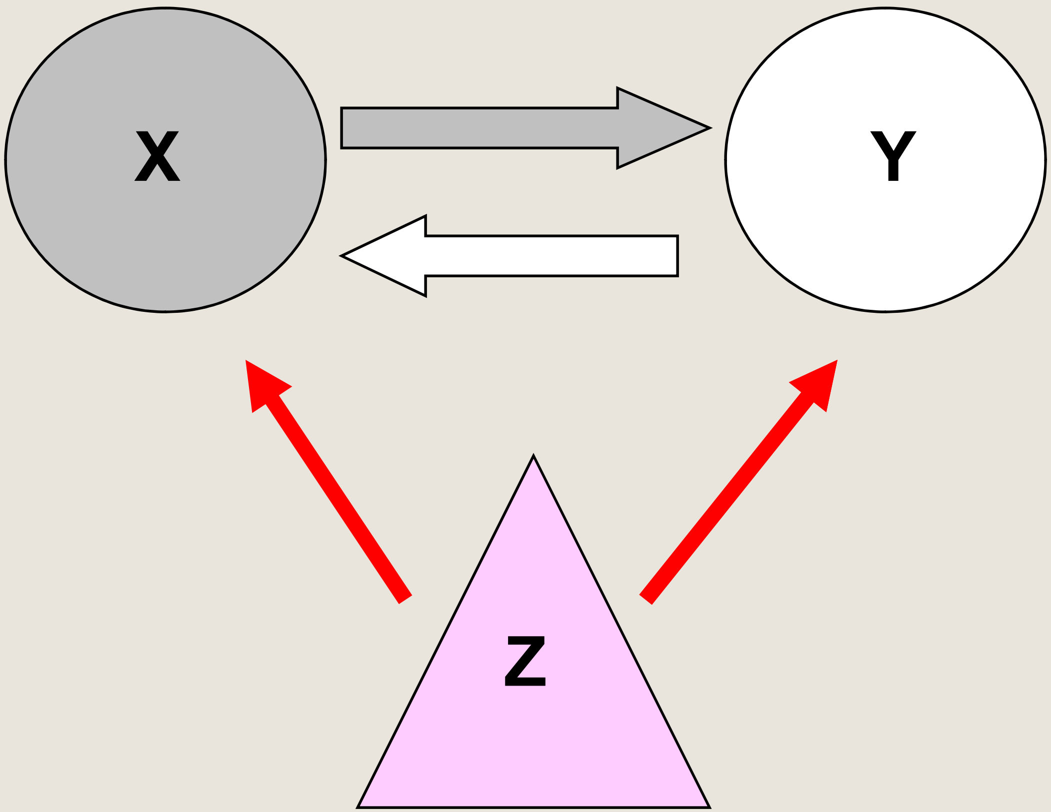
- You are given a choice between taking two courses:
  - Physics
    - Everybody in the class gets B
  - Math
    - Your grade depends on your final exam

- Which course would you choose?
- What does this tell you about yourself?
- In which course are you likely to study harder?

Causality and Correlation

- Piece rate workers should be more productive.
- This is because:
  1. Piece rate causes workers to be more productive (incentive effect); and/or
  2. More productive workers select to work for piece rate firms (selection effect)
- Causality vs. Correlation
  - Cities with more doctors have more sick patients.
  - Cities with more cops have higher crime rates.

Suppose X and Y are correlated. Three possibilities:



Cause and Effect Questions in Economics

- Does piece rate pay improve productivity?
- Other examples:
  - Does education increase earnings?
  - Does training reduce poverty?
  - Do minimum wage laws increase unemployment?
  - Does class size affect learning?
  - Do divorce laws affect domestic violence?
- All these questions of the same form:

  Does X cause Y?
- Correlation vs. causation problem implicit in all questions

3. Rubin Causal Model

- Useful tool to:
  1. Precisely define what it means to say that X causes Y;
  2. Understand fundamental identification problem that plagues all empirical studies;
  3. Serves as a basis for evaluating all empirical studies by providing a unified framework.

Definition of Causality

- Let:
  - y_i^1 = outcome for individual *i* if treated
  - y_i^0 = outcome for individual *i* if not treated

- Then:
  - $y_i^1 - y_i^0$ is the causal effect of X for individual *i*
  - $E[y_i^1 - y_i^0]$ is the average causal effect (for all *i*)

Actual and Counterfactual Outcomes

- Problem:
  - For treatment group (d_i=1) we observe y_i^1 but not y_i^0
  - For control group (d_i=0) we observe y_i^0 but not y_i^1

$\Rightarrow$ We can never know the causal effect of X on Y!

- Possible Solution:
  - Use y_i^0 for control group to approximate y_i^0 for treatment group

$$E[y_i^1|d_i=1]-E[y_i^0|d_i=0]$$

Naïve Comparison

$E[y_i^1|d_i=1]- E[y_i^0|d_i=0]$

$=E[y_i^1|d_i=1]-E[y_i^0|d_i=0]+E[y_i^0|d_i=1]-E[y_i^0|d_i=1]$

$=\{E[y_i^1|d_i=1]-E[y_i^0|d_i=1]\}+\{E[y_i^0|d_i=1]-E[y_i^0|d_i=0]\}$

- $E[y_i^1|d_i=1]- E[y_i^0|d_i=1]$ = true casual effect
- $E[y_i^0|d_i=1]-E[y_i^0|d_i=0]$ = selection bias
  - Difference in outcome between treatment and control group even if they both received no treatment

Fundamental Identification Problem

$$E[y_i^0|d_i=1]=E[y_i^0|d_i=0] \text{ ???}$$

- How to make sure that treatment and control groups are sufficiently similar (compare apples to apples)?
- All empirical studies face this problem

Example

- y = productivity
- d=1 if piece-rate pay (treatment), d=0 if salary
- Outcomes:

  $y_i^0 = \alpha + u_i$

  $y_i^1 = \alpha + \beta + u_i$

  - where u_i = individual-specific productivity
- Causal effect = $y_i^1 – y_i^0 = \beta$
- Naïve comparison yields:

  $E[y_i|d_i=1]-E[y_i|d_i=0]= \beta+ E[u_i|d_i=1]-E[u_i|d_i=0]$

	y_i^0	y_i^1
Piece Rate (d_i=1)	20	**25**
Salary (d_i=0)	**5**	10

- Causal effect = (25-20)=5
- Observed difference is 25-5=20
  - Part of this is treatment effect (5)
  - Part of this is selection effect (20-5=15)

4. Randomized Experiments

- The most credible empirical strategy
- Individuals randomly assigned to treatment and control groups (e.g. by flipping a coin)
- Random assignment ensures that:

$$E[y_i^0|d_i=1]=E[y_i^0|d_i=0]$$

  - Treatment and control groups similar in all aspects except for treatment

	Salary	Piece Rate
High Ability	20	25
Low Ability	5	10

- Randomize individuals into salary and piece rate firms

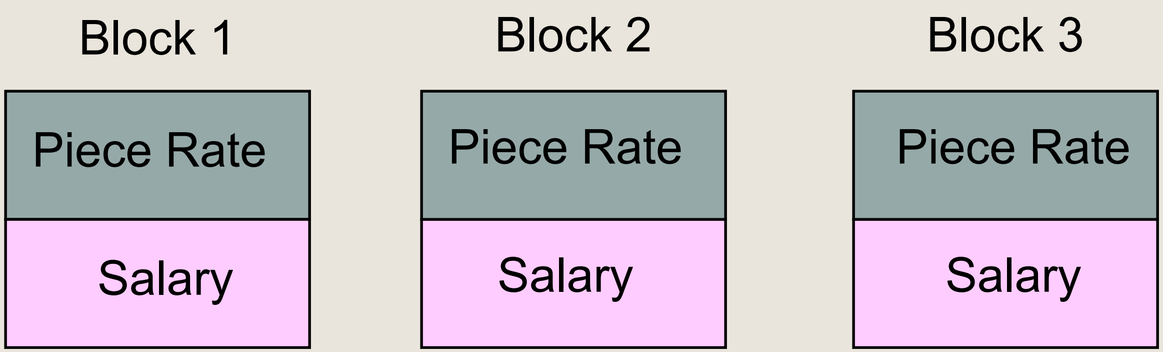
•E[y|Salary] = 0.5(20)+0.5(5)=12.5
•E[y|Piece Rate] = 0.5(25)+0.5(10)=17.5

•E[y|Piece Rate]-E[y|Salary]=5=Causal Effect!

Application: Shearer (2000) – Tree Planting

Experimental Design

- Nine workers randomly selected from the firm
- Three plots of land, different in terms of planting conditions
- Each plot divided into two parts: piece rate pay and salary
- At the beginning of a day, each worker randomly assigned to one plot and type of pay



Controlling for Other Factors

- Possible differences between piece rate and salary workers that may affect their productivity:
  - Workers not informed about experiment
  - Male workers only
  - Length of work day constant
  - Blocks of land large enough
  - Same supervisor for all workers

Experimental Results

	Obs.	Piece Rate (Mean Trees)	Salary (Mean Trees)	Percent Difference
All Plots	120	1,256	1,037	21.1%
Plot 1	24	1,390	1,157	19.3%
Plot 2	48	1,501	1,142	31.4%
Plot 3	48	944	873	8.1%

- **Piece rate workers about 20% more productive than salary workers.**

Limitations of Randomized Experiments

1. Sometimes Difficult or Impossible to Implement
   - Monetary Costs
   - Ethical and Legal Considerations
     - Randomize people into smoking (treatment) and non-smoking (control) groups to study impact of smoking on health
     - Randomly annul marriages to assign children to either married parents group (treatment) or single parent group (control) to study impact of divorce on children's psychological development
2. External Validity
   - Do the results generalize from the unique and idiosyncratic settings, procedures and participants to other populations and conditions?

Summary

1. Correlation does not necessarily imply causation.
2. The fundamental identification problem arises because for any individual we observe only the actual outcome.
3. Naïve comparison of outcomes for treatment and control groups is often subject to selection bias because the outcome for these groups would be different even in the absence of treatment.
4. Randomized experiments randomize subjects into treatment and control groups which helps to minimize the selection bias problem.