

**Lecture 9: Why has the rate of return to education increased?**

**Questions from last lecture:**

Q: How is the delay in payoff to a GED for whites explained?

A: Perhaps employers are looking at the GED signal and the HS dropout signal. They pay lower wages to a GED holder until the employee can prove himself. Alternatively, HS dropouts may get GEDs when the job market is bad to distinguish themselves and the value of their time is particularly low.

Q: What is the motivation for the Tyler, Murnane and Willett paper?

A: The GED is a relatively costly program. They want to know whether its worthwhile for the individual and for the US. Prior to this study, the literature had found that GED holders and HS dropouts earned the same wages. They are trying to run a more refined version of older experiments.

**Continued from last lecture:**

For white males, the GED has a \$1473 signaling value with a standard error of \$678. The average earnings of group 4 is \$8500.

	<u>States</u>	
	Treatment	Control
Group 4	A	B
Groups 5-10	C	D

(A-B)= the GED effect + the state economy effect

(C-D)= the state economy effect

(A-B)-(C-D)= the GED effect alone

In the paper, this differences-in-differences calculation is done separately for whites and minorities.

For black males:

	<u>States</u>	
	Treatment	Control
Group 4	GED	No GED
Groups 5-	GED	GED

(A-B)-(C-D)= \$-1357, standard error of 906.

What does the \$-1357 mean? With the standard error, the solution isn't statistically significant. Why? A high percentage of minority males who get the GED are in jail or have a criminal record, meaning they either can't work or get paid lower for reasons other than having a GED vs. no GED. Additionally, GEDs completed in government programs may or may not have been completed voluntarily.

Can we just drop the prison data and rerun the regression analysis? No. We only know of prison records in Florida data, not other states.

**Murnane, Willett, and Levy paper:**

Motivation:

	<u>1969</u>	<u>1976</u>	<u>1980</u>	<u>1985</u>
(Median 25-34 college grad earnings, male) / (Median 25-34 HS grad earnings,male)	1.42	1.3	1.3	1.48

During the 1970s, there was a very large supply of college grads in the job market. There was a decrease in college educated worker wages. Additionally, there was an increase in high school education workers wages.

The authors were looking to give concrete meaning to what skills economy values.

$$\ln(\text{wage})_i = \alpha_0 + \beta_1 (\text{yearsED})_i + \beta_2 (\text{MathScore})_i + \varepsilon_i$$

2 samples were collected by the Department of Labor:

- 1) a. HS seniors, 1972: background info and math test scores at age 18
  - b. Original HS seniors, at age 24 in 1978: wage data
- 2) a. HS seniors, 1980: background info and math test scores at age 18
  - b. 2<sup>nd</sup> group of HS seniors at age 24 in 1986: wage data

With these two samples, we cover the two huge changes in the college-HS wage cap in the 1970s and in the 1980s.

What do you want to test using this data?

~Do basic math scores affect wages? Did this effect change?  $\beta_2$  should be larger in the second sample since we believe skills became more important.

~Say education is just acting as a signal, how would that show up in the regression? The math score wouldn't be significant. However, with this regression we wouldn't be able to tell whether education was just a signal or whether it provided useful skills.  $(\text{yearsED})_i$  is a very crude measure of education compared to other papers we've been looking at.

~How are we dealing with ability bias? We are using the math score before college as a proxy for ability, which isn't a perfect measure.

Every person in the data at least graduated from high school.

	<u>Wage, 1978</u>	<u>Wage, 1978</u>		<u>Wage, 1986</u>	<u>Wage, 1986</u>
<b>Males</b>			<b>Males</b>		
<b>Years of College</b>	0.022	0.013	<b>Years of College</b>	0.044	0.021
<b>t-statistics</b>	(3.63)	(1.85)	<b>t-statistics</b>	(5.72)	(2.22)
<b>Math scores</b>	----	0.004	<b>Math scores</b>	----	0.011
<b>t-statistics</b>	----	(3.13)	<b>t-statistics</b>	----	(5.06)

See the paper for the results for females.

$\beta_1$  decreased in regressions that included math scores for both time periods, as we expected. Again,  $\beta_2$  is larger in the second group of people than in the first groups of people, implying that skills are valued more in 1978 than in 1986.

If we run the regression only for high school graduates, we find that math scores have statistically insignificant effect on wages at age 19 or 20 and a statistically significant effect on wages at age 24.

Why? When a high school graduate is first hired out of high school, their wage is based only on their high school degree and not on any skills or ability they may possess. With more time in the labor force, a high school graduate can prove their skills and ability and boost their wages.

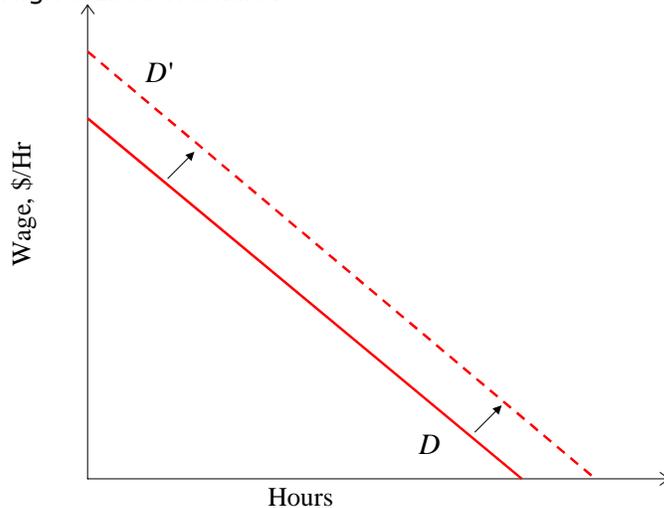
From the point of view of a student not planning on attending college, she is given very little incentive to study and learn basic skills because HS students heavily discount the future so they don't value the increase in wages that occurs years after HS that is attributable to skill/ability.

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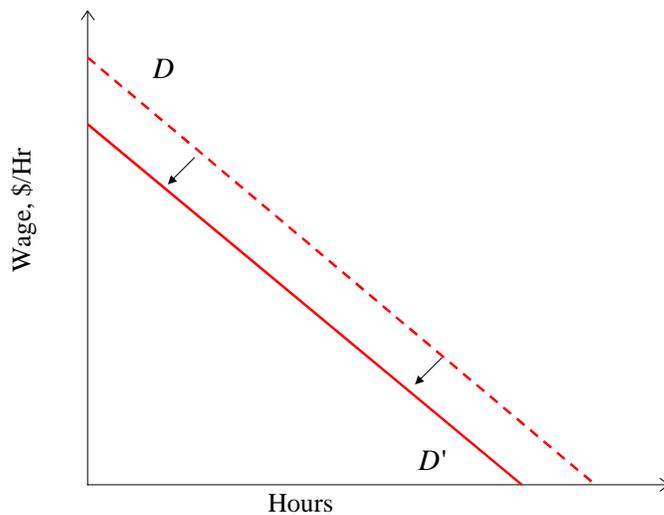
### **Computers and Work:**

Generally, people assume that computerization/offshoring puts the least skilled workers at risk. This is not true. Generally, it is the lower to middle skilled jobs that are at risk.

High skilled workers:



Low skill workers:



How is it that computers change occupational demand?  
It can substitute for or complement labor.

Examples:

- 1) Airport boarding pass kiosks → substitution
- 2) MIT general number speech interface → substitution
- 3) Image guided surgery → complement

How do we lay out a theory that explains what tasks/jobs can be substituted for and what tasks/jobs can be complemented?

- 1) All human work involves the processing of information
- 2) Computers execute rules

What kind of tasks involve information processing that can be expressed in rules?

Deductive rules: things we can write down from the nature of the process, a series of rules

Inductive rules: equations generated from statistical models from training sample data, pattern recognition i.e. credit card companies monitor transactions and flag accounts that have statistically abnormal activity.

Ease of programming:

With deductive rules, you can just write the set of rules into a program.

With inductive rules, you need to execute statistical estimation.

There are also both high and low skills tasks for which you can't estimate or articulate the rules such as litigation and janitorial work.

As we said earlier, most substitution occurs in the lower-middle of the skill distribution.

In reality, specific tasks rather than a whole job is computerized.

Herbert Simon: Stated that you can cut down the programming burden by routinizing the context of a job. For example, at Amazon, instead of having customers send an email stating what they want to order, there is a standardized order form, making the process much simpler for Amazon.