Econometrics I

Lecture 5: Extended Example: The Wage Equation

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Fall 2025

Mincerian Regression

- Recall the Mincerian regression (wage equation):

$$\ln wage_i = \beta_0 + \beta_{ed} Education_i + \beta_{exp} Experience_i + \beta_{Fem} Female_i + \cdots + \varepsilon_i$$

- Let's revisit estimating this with the Cornwell and Rupert (NLSY) data.

Process the data

```r
suppressMessages(library(tidyverse))
suppressMessages(library(fixest))

# first, the Cornwell and Rupert regression
data <- read.csv('./cornwell-rupert.csv') %>% mutate(EXP2 = EXP^2)

# see counts of each education level

data2<-data %>% mutate(ED_LEVEL=cut(ED,c(0,8,11,12,15,16,17),
                      labels = c("NOHS", "SOMEHS", "HS", "SOMECOL","COL","POST"),
                      right=TRUE))

# check that we did it correctly
table(data$ED,data2$ED_LEVEL)
```

Baseline Results

```r
reg_1 <- feols(LWAGE ~ ED + EXP + EXP2 + WKS + OCC + SOUTH + SMSA
  + MS + UNION + FEM, data = data)

# dropping the constant
reg_2 <- feols(LWAGE ~ -1 + i(ED_LEVEL) + EXP + EXP2 + WKS + OCC + SOUTH + SMSA
         + MS + UNION + FEM, data = data2)

# not dropping the constant -- which category is omitted?
reg_3 <- feols(LWAGE ~ 1+ i(ED_LEVEL) + EXP + EXP2 + WKS + OCC + SOUTH + SMSA
        + MS + UNION + FEM, data = data2)

# change the omitted category -- how do coefficients change?
reg_4 <- feols(LWAGE ~ 1+ i(ED_LEVEL,ref="COL") + EXP + EXP2 + WKS + OCC + SOUTH + SMSA
         + MS + UNION + FEM, data = data2)
etable(list(reg_1,reg_2,reg_3,reg_4))
```

Note on interpreting effects with log dependent variable:

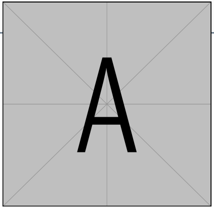
Intrepreting coefficients for $\log(y_i) \approx 1 + \beta$:

- $\exp(-.3892) = .6826$
- $\exp(.05654) = 1.057$

Dependent Variable:	LWAGE			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	5.245^{***}		5.655^{***}	6.161^{***}
	(0.0717)		(0.0634)	(0.0597)
ED	0.0565^{***}			
	(0.0026)			
EXP	0.0404^{***}	0.0410^{***}	0.0410^{***}	0.0410^{***}
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
EXP2	-0.0007^{***}	-0.0007^{***}	-0.0007^{***}	-0.0007^{***}
	(4.78×10^{-5})	(4.8×10^{-5})	(4.8×10^{-5})	(4.8×10^{-5})
WKS	0.0045^{***}	0.0046^{***}	0.0046^{***}	0.0046^{***}
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
OCC	-0.1405^{***}	-0.1386^{***}	-0.1386^{***}	-0.1386^{***}
	(0.0147)	(0.0151)	(0.0151)	(0.0151)
SOUTH	-0.0721^{***}	-0.0762^{***}	-0.0762^{***}	-0.0762^{***}
	(0.0125)	(0.0126)	(0.0126)	(0.0126)
SMSA	0.1390^{***}	0.1436^{***}	0.1436^{***}	0.1436^{***}
	(0.0121)	(0.0121)	(0.0121)	(0.0121)
MS	0.0674^{***}	0.0692^{***}	0.0692^{***}	0.0692^{***}
	(0.0206)	(0.0207)	(0.0207)	(0.0207)
UNION	0.0901^{***}	0.0940^{***}	0.0940^{***}	0.0940^{***}
	(0.0129)	(0.0130)	(0.0130)	(0.0130)
FEM	-0.3892^{***}	-0.3819^{***}	-0.3819^{***}	-0.3819^{***}
	(0.0252)	(0.0253)	(0.0253)	(0.0253)
ED_LEVEL = NOHS		5.655^{***}		-0.5066^{***}
		(0.0634)		(0.0284)
ED_LEVEL = SOMEHS		5.795^{***}	0.1400^{***}	-0.3666^{***}
		(0.0624)	(0.0249)	(0.0236)
ED_LEVEL = HS		5.903^{***}	0.2482^{***}	-0.2584^{***}
		(0.0609)	(0.0229)	(0.0194)
ED_LEVEL = SOMECOL		5.991^{***}	0.3364^{***}	-0.1702^{***}
		(0.0610)	(0.0268)	(0.0206)
ED_LEVEL = COL		6.161^{***}	0.5066^{***}	
		(0.0597)	(0.0284)	
ED_LEVEL = POST		6.188^{***}	0.5337^{***}	0.0271
		(0.0589)	(0.0295)	(0.0213)
Fit statistics				
Observations	4,165	4,165	4,165	4,165
R^2	0.41826	0.41724	0.41738	0.41738

Heuristic Policies

- These are methods aiming to give a good but not necessarily optimal solution to a problem.
- There exist a number of such policies for bandit problems.
- Greedy policy:
  - choose arm with greatest expected reward
  - ignores variability in prior distribution
  - quite good for Bernoulli bandits, but less effective for normal bandits



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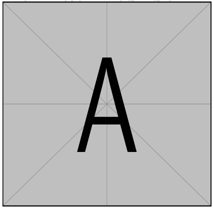
$(\alpha, \beta) = (1, 1)$



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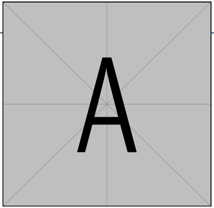

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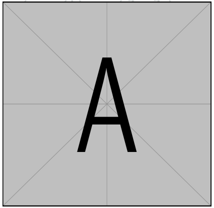

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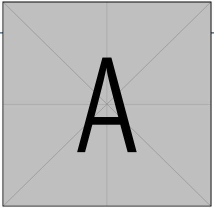

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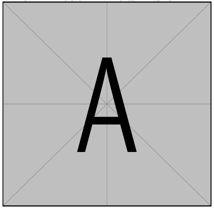

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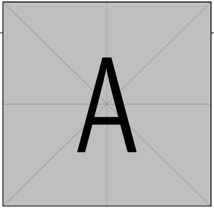

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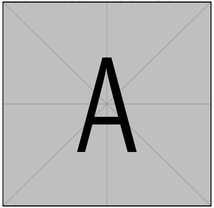

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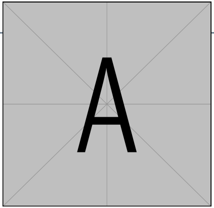

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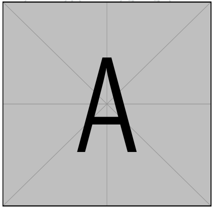

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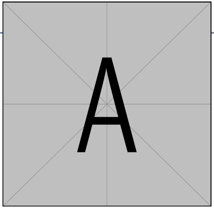

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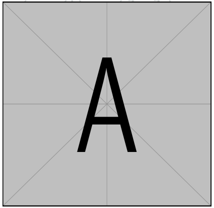

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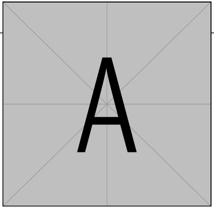

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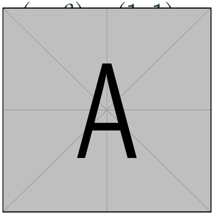

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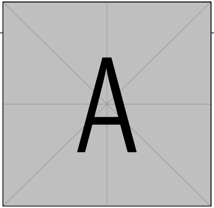

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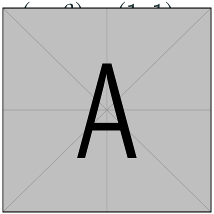

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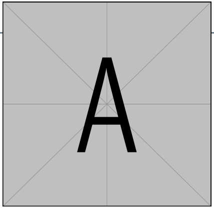

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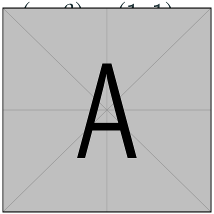

$\Longrightarrow$ play this arm

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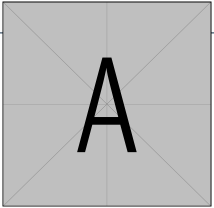

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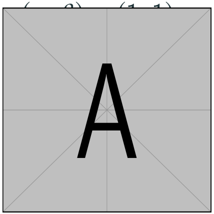

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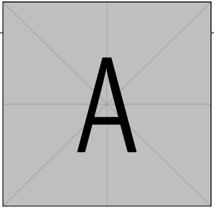

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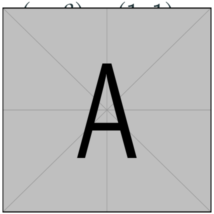

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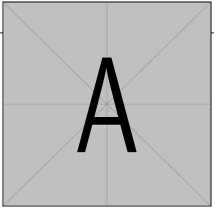

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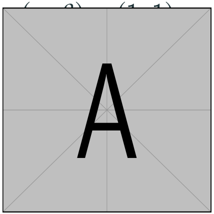

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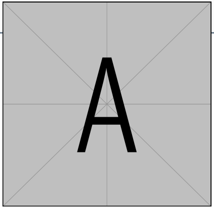

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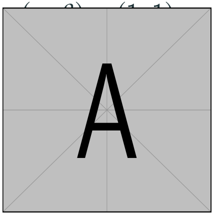

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$(\alpha, \beta) = (6, 5)$

$\Longrightarrow$ play this arm with probability ε

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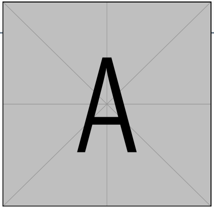

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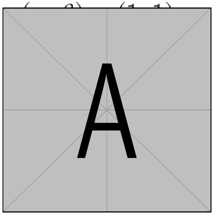

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play this arm with probability $1 - \varepsilon$

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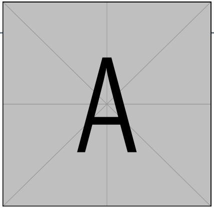

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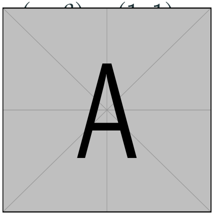

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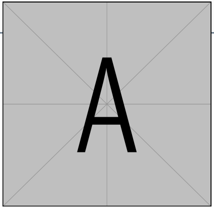

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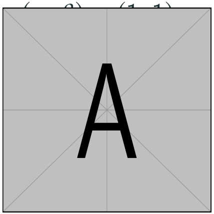

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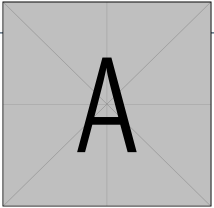

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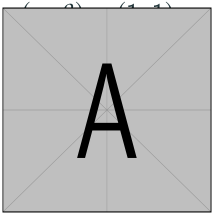

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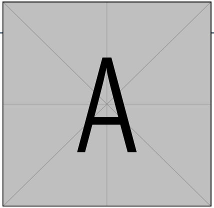

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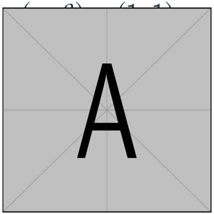

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