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## 14.771 Development Economics: Microeconomic issues and Policy Models

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# 14.771: Labor Lecture 2

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- Migration
  - International migration and wage differentials
  - Networks among migrants

# Migration across countries

- Wage differences across countries are vast, and suggest massive inefficiencies
  - ILO (1995) reports that the wage of a construction carpenter in India was \$42 per month (\$250 or so at PPP), vs. \$2200 in the US.
  - How much of this is difference in skill and how much a difference in the role of other inputs and/or TFP?
  - To the extent it is other inputs and/or TFP, there is a first order gain in efficiency when you move the carpenter to the US.
- However there is also a brain-drain/brain-gain:
  - Complementary factors capture part of the gain in the destination countries. Close substitutes lose.
  - Complementary factors lose in the sending countries.
  - So wage differences do not exactly predict the magnitude of total general equilibrium changes we would expect if we allowed full migration

# The skill price and migration

- A simple way to think about these issues is to think of a 'skill price', i.e.,

- Person  $j$  in country  $i$  earns a wage  $W_{ij} = w_i x_{ij}$  where  $w_i$  is the skill price in country  $i$  and  $x_{ij}$  is  $j$ 's amount of skill.
- People migrate from  $i$  to  $u$  if

$$w_u x_{ij} - C_i \geq w_i x_{ij}.$$

where  $C_i$  is the cost of migration from that country to country  $u$  (for U.S.)

- So migration occurs if

$$x_{ij} \geq \frac{C_i}{w_u - w_i}$$

- This simple framework has several implications
  - 1 Only the most skilled people from a given country will migrate.
  - 2 The higher the skill price of a sending country ( $w_i$ ), the higher is the skills of the migrants from that country.
  - 3 The harder it is to get to the US from that particular country ( $C_i$ ), the higher is the skill level of those who migrate from that country.

# Estimating the skill price in theory

- We would like to estimate these skill prices to test models of cross-country migration
- How can one estimate the skill price?
- Assume that

$$x_{ij} = \exp[\beta_i(Q_i)S_{ij} + \sum_k \gamma_{jk}I_{ijk} + \mu_{ij}]$$

is the skill production function, where  $S_{ij}$  is the years of schooling,  $\beta_i(Q_i)$  is the return on schooling as a function of quality of schooling in that country, and  $I_{ijk}$  is a set of other human capital attributes.

- Wages in a given country are determined by

$$W_{ij} = w_i x_{ij}$$

and hence

$$\log W_{ij} = \log w_i + \beta_i(Q_i)S_{ij} + \sum_k \gamma_{ijk}I_{jk} + \mu_{ij}.$$

- The intercept of this equation is the skill price.

# Estimating the skill price in practice

- The problem is that to estimate this equation, one needs comparable micro data on wages, schooling, and other human capital variables for a large sample of countries.
- This does not appear to exist.
- Rosenzweig (2007) proposes an alternative – examining migrants who are in the US.
- He (and others) collected a dataset called the "New Immigrant Survey", which provides comparable data on immigrants from 140 countries on the last job they had before they came to the U.S.
- What are the pitfalls of this approach?
  - Selective sample into migration: model implies immigrants positively selected on unobservables. Why is this a problem?
  - Selective sample of countries: only those with sufficient immigrants in U.S. Why is this a problem?

# Empirical note: the Heckman Selection Correction

- Selective sample into migration implies that  $w_i$  is biased upwards, because you are more likely to be in the sample if you have high unobservables.
- Rosenzweig deals with this using a Heckman selection model:
  - Our migration model from earlier implies that migration is a function of determinants of country skill price (GDP, quantity of skills) and migration costs (distance):

$$\Pr(\text{migrate} = 1) = \Pr(X'\gamma + v > 0)$$

where  $v$  is Normal and has correlation  $\rho$  with  $\mu$  (error from wage equation).

- The selection issue is we estimate the wage equation conditional on migrating, i.e., conditional on  $X'\gamma + v > 0$ .
- Since  $\mu$  and  $v$  are correlated, this implies that

$$\log W_{ij} = \log w_i + \beta_i(Q_i)S_{ij} + \sum_k \gamma_{ijk}I_{jk} + E\left(\mu_{ij} \mid X'\gamma + v > 0\right).$$

- If both  $v$  and  $\mu$  are normal, then the conditional expectation is given by the Mills ratio:

$$E\left(\mu_{ij} \mid X'\gamma + v > 0\right) = \rho \frac{\phi(X'\gamma)}{\Phi(X'\gamma)}$$

- So we first estimate migration as a function of gdp, schooling levels, and migration costs:

$$\Pr(\text{migrate} = 1) = \Pr(\alpha + \beta_1 Y + \beta_2 S + \beta_3 C + v > 0)$$

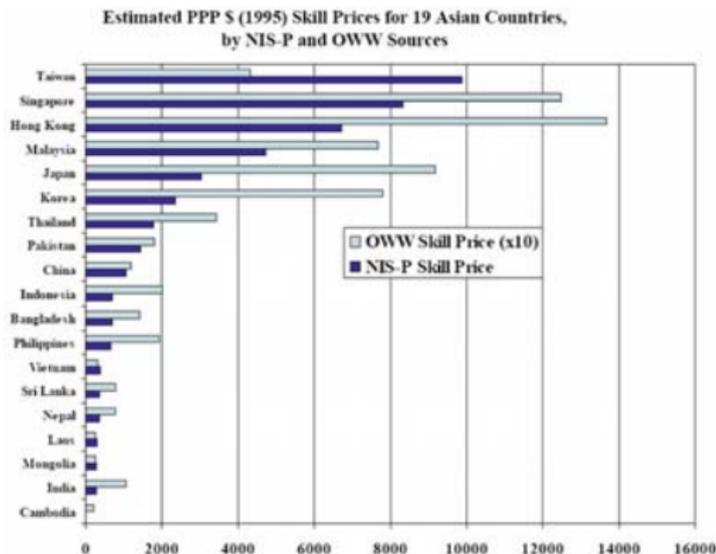
- And then use the resulting coefficients to estimate:

$$\log W_{ij} = \log w_i + \beta_i(Q_i)S_{ij} + \sum_k \gamma_{ijk} I_{jk} + \rho \frac{\phi(\alpha + \beta_1 Y + \beta_2 S + \beta_3 C)}{\Phi(\alpha + \beta_1 Y + \beta_2 S + \beta_3 C)}$$

- Note:
  - If the same variables are in the main equation and the selection equation, you are entirely identified off function form.
  - More generally functional form matters a lot, so we prefer not to rely on these types of models.

# Estimates of skill prices

- Skill prices differ significantly across countries
  - Skill price in S. Korea is 3.5 to 5.5 times that in Bangladesh! Taiwan is 20 times Bangladesh!



Courtesy of Mark Rosenzweig. Used with permission.

# Determinants of skill price

- First estimate migration equation (do you migrate to US).
  - More migrants if your GDP is lower, if you are closer to the US, if there is more schooling in your country (which lowers skill price)

<b>Determinants of the Probability of Immigration (NIS)</b>		
<i>Origin-country variable</i>		
PPPS GDP per worker ( $\times 10^{-3}$ )	-.0129 (3.44)	-.0126 (3.56)
Average adult schooling attainment	.0463 (2.64)	.0576 (3.80)
Distance to the United States ( $\text{miles} \times 10^{-3}$ )	-.0901 (5.60)	-.0985 (7.62)
US military base in country	.205 (2.46)	.177 (2.46)
Any ranked universities	-.225 (1.08)	-.214 (1.28)
Average rank of ranked universities	.000406 (0.25)	.000463 (0.34)
Teacher/pupil ratio in secondary schools	--	.00810 (1.59)
Teacher/pupil ratio in primary schools	--	.00368 (1.66)

Figure by MIT OpenCourseWare.

# Determinants of skill price

- Estimate skill price equation using migration equation to correct for selection bias
  - Note that the variables are the same except distance to US – so distance to US (and functional form) is being used to identify selection
  - GDP increases skill price; more skilled labor decreases skill price

Estimates of the Determinants of the Country Log Skill Price		
Sample	US immigrant home wages (NIS-P)	
Variable/Estimation procedure	GLS	GLS-SC
<i>Country characteristics:</i>		
Log GDP per worker	1.41 (5.01)	1.35 (5.21)
Log mean schooling	-1.77 (3.18)	-1.97 (3.23)
Log teacher-pupil ratio, primary schools	-1.90 (3.68)	-2.17 (3.80)
Log teacher-pupil ratio, secondary schools	1.44 (2.51)	1.36 (2.56)
<i>Immigrant skill characteristics:</i>		
Schooling	.0683 (3.50)	.0745 (3.79)
Age	.0428 (4.32)	.0436 (4.50)
Mills ratio	-	.800 (1.46)

Figure by MIT OpenCourseWare.

# Determinants of skill level of migrants

- More educated migrants from higher skill price countries, farther countries

<b>Determinants of the Log Average Schooling Attainment of New Adult Immigrants, by Type (NIS)</b>			
<i>Origin-country variable/immigrant type</i>	<i>Employment visa principals</i>	<i>EVPS's + spouses of citizens</i>	<i>All</i>
Log skill price	.499 (2.83)	.254 (1.98)	.139 (0.84)
Log real GDP per adult-equivalent	-.108 (1.60)	-.0116 (0.27)	.0557 (0.85)
Log distance of country to the United states	.0377 (4.43)	.0356 (4.53)	.0414 (3.89)
US military base in country	-.0220 (0.41)	-.0449 (1.39)	-.0127 (0.30)
English an official country language	.115 (1.62)	.0812 (2.84)	.120 (3.91)
Any ranked universities	1.18 (2.80)	.492 (1.78)	.115 (0.32)
Average rank of ranked universities	-.0110 (2.86)	-.00496 (1.77)	-.00162 (0.46)
Log teacher/pupil ratio in secondary schools	.00480 (0.15)	-.0230 (0.79)	.0380 (1.00)
Log teacher/pupil ratio in primary schools	-.00985 (0.08)	.0452 (1.10)	.0249 (0.40)

Figure by MIT OpenCourseWare.

- Suggests that basic simple model of migration is explaining number and selection of migrants
- But data issues suggest this is far from the end of the story...

## Networks - Munshi (2003)

- The simple model above assumed that the skill price was constant, and available to everyone – all you need to do is show up and you get the new wage
- In practice, labor markets are much more complicated, and people use networks to integrate themselves into economy in the new location.
- Some quotes from Munshi's paper:
  - "Leonardo shared an apartment with seven other friends, all paisanos from Sinaloa. Seven of the eight friends worked as gardeners. The first two friends had been in the area for five years, and provided referrals for employers for each of the subsequent migrants, the last of whom migrated two years earlier."
  - "Over 70 percent of the undocumented Mexicans, and a slightly higher proportion of the Central Americans, that Chavez interviewed in 1986 found work through referrals from friends and relatives."

- Setting: migrants from Mexico to the US
- Question: what role do networks play in integrating migrants into the workforce?
- Empirical problem: If we observe that people from a village always go to the same place, it could be because they have common skills and there is a demand for those skills in that location.
- Munshi's solution:
  - Use lagged rainfall shocks at the origin location to instrument for the size of the network
  - Use individual fixed effects for migrants to control for selection in ability
- Data from the Mexican Migration Project

# First stage: rainfall and migrants in US

- More new migrants ( $\leq 3$  years) when recent rainfall low. More established migrants ( $> 3$  years) when old rainfall is low.

Dependent variable:	Reduced-form				First-stage		
	Employment at the destination		Employment at the origin		New migrants	Established migrants	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Recent-past rainfall	-0.028 (0.027)	-0.049 (0.035)	-0.023 (0.072)	-0.047 (0.040)	0.085 (0.018)	-0.091 (0.037)	0.005 (0.020)
Distant-past rainfall	-0.125 (0.035)	-0.092 (0.027)	-0.226 (0.108)	-0.129 (0.044)	0.046 (0.021)	0.103 (0.033)	-0.106 (0.023)
Individual fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$R^2$	0.705	0.705	0.647	0.038	0.812	0.768	0.940
Q statistic	0.041	0.041	0.036	0.660	2.813	0.010	0.316
Number of observations	4546	4546	1732	4546	41,120	4546	4546

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## Reduced form: rainfall and employment

- Recent rainfall has no effect on employment in US. Lagged rainfall has positive effect on US employment.
  - Also true when looks only at migrants who have arrived in past 1 or 2 years (column 3) though not much variation left after individual FE removed

Dependent variable:	Reduced-form				First-stage		
	Employment at the destination		Employment at the origin		New migrants	Established migrants	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Recent-past rainfall	-0.028 (0.027)	-0.049 (0.035)	-0.023 (0.072)	-0.047 (0.040)	0.085 (0.018)	-0.091 (0.037)	0.005 (0.020)
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## IV: employment

- Large effects of network size on probability of employment

	Employment				
	OLS				
	Basic specifications				
Dependent variable:	(1)	(2)	(3)	(4)	(5)
New migrants	-0.032 (0.070)	0.397 (0.315)	0.522 (0.376)	0.093 (0.537)	0.626 (0.501)
Established migrants	0.670 (0.154)	1.554 (0.551)	1.474 (0.545)	2.073 (1.069)	1.745 (0.661)
Individual fixed effects	Yes	Yes	Yes	Yes	No
Year dummies	Yes	Yes	Yes	Yes	Yes
$R^2$	0.707	—	—	—	—
Q statistic	0.042	0.041	0.041	0.036	0.660
Number of observations	4546	4546	4546	1732	4546

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# IV: occupation

- Large effects of network size on probability of employment

Dependent variable:	Occupation at the destination			Occupation at the origin	Occupatio	
	Reduced-form				OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Recent-past rainfall	-0.125 (0.077)	-0.026 (0.217)	-0.025 (0.096)	0.011 (0.015)	—	—
Distant-past rainfall	-0.223 (0.086)	-0.479 (0.258)	-0.185 (0.098)	-0.027 (0.019)	—	—
New migrants	—	—	—	—	0.398 (0.231)	1.592 (0.928)
Established migrants	—	—	—	—	0.256 (0.247)	3.585 (1.339)
Individual fixed effects	Yes	Yes	No	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
$R^2$	0.825	0.734	0.143	0.898	0.825	—
$Q$ statistic	0.319	0.007	1.605	1.886	0.322	0.319
Number of observations	4240	1588	4240	30,917	4240	4240

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# Limits to migration

- For international migration, limits are easy to understand: there are legal limits
  - Though who these limits benefit or hurt is an important question in the US labor literature – see Borjas, Card, Cortes, etc.
- For domestic migration, though, legal limits are usually not present
- But there may be other important limitations.
- Credit
  - Banerjee-Newman (1998) suggest that People in rural areas have access to informal insurance mechanisms, but when you migrate to an urban area, you lose this. This implies that migration will occur at the low end (where you have no collateral at all, so can't borrow either way) or at the high end (where you don't need informal insurance)
  - Munshi and Rosenzweig (2005) test these ideas in rural India
- Networks (same argument as Munshi applies domestically as well)
- Land market imperfections
- Behavioral issues