Economics 270c

Development Economics

Lecture 15 – May 1, 2007

Lecture 1: Global patterns of economic growth and development (1/16)

The political economy of development

Lecture 2: Inequality and growth (1/23)
Lecture 3: Corruption (1/30) – Guest lecture by Ben Olken
Lecture 4: History and institutions (2/6)
Lecture 5: Democracy and development (2/13)
Lecture 6: Ethnic and social divisions (2/20)
Lecture 7: Economic Theories of Conflict (2/27)
Lecture 8: War and Economic Development (3/6)

Human resources

Lecture 9: Human capital and income growth (4/3)
Lecture 10: Increasing human capital (4/10)
Lecture 11: Health and nutrition (3/13)
Lecture 12: The Economics of HIV/AIDS (3/20)
Lecture 13: Labor markets and migration (4/17)

Lecture 14: Environment and development (4/24)
☆ **Lecture 15: Social Learning and Technology Adoption (5/1)**

- Today – beer and pizza at LaValls after class (5:30pm)
- Final exam in class next Tuesday May 8th (3:30pm). The research proposal is due next week, too
- How did students on the job market do?

  -- Emily Oster, University of Chicago (Economics)

  -- Masa Kudamatsu, Stockholm University (IIES)

  -- Karthik Muralidharan, UCSD (Economics)

Lecture 15 outline

(1) Social learning and technology adoption in development economics: key questions and issues

(2) Learning about new agricultural technologies – the Green Revolution in India (Foster and Rosenzweig 1995)

(3) "Failed" social learning: the case of deworming (Kremer and Miguel 2006)

(1) Social learning and technology adoption

- Economic development leads to massive transformations in life. Part of this transformation is the incorporation of tremendous amounts of new information, practices, and technologies into their lives

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- Are mainstream economics tools appropriate for less developed countries: “poor and irrational” vs. “poor but rational” debate in the 1950s-1960s
- Why don’t individuals adopt technologies and practices that appear to be overwhelmingly beneficial to them? Why does social learning fail? Agriculture, health, family planning technologies

(1) Social learning and technology adoption

- Famous work in economics and sociology (Zvi Griliches on hybrid corn, James Coleman on doctors' prescription decisions, Everett Rogers 1995 survey)

- Many anomalies have been documented:

  -- Agriculture: Why don't people adopt high value cash crops? Use fertilizer and hybrid seeds?

  -- Health: Why don't people vaccinate their children? Wash their hands? Practice safe sex?

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- Spillovers in technology adoption may justify public subsidies (e.g., agricultural extension activities)

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  (4) Agency problems within the household, i.e., failed bargaining over the returns to an investment, may prevent adoption (Udry 1995)

(1) Social learning and technology adoption

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  (3) Disentangling the channels: is pure imitation the key channel? Or learning about the benefits of the technology per se? Or learning to use the technology?

(1) Social learning and technology adoption

- Other questions in the literature:

  (1) Endogenous network formation: who becomes friends with / a work partner with whom? How do exogenous economic shocks (e.g., job loss) affect individuals' social networks?

  (2) In a related question: how much do people invest in social ties? How "expensive" is the creation of a social link that has economic returns? (This is of general social science interest, beyond development economics)

(2) Foster and Rosenzweig (1995, *JPE*)

- The most influential empirical social learning study in development economics

- Study the adoption of high yield variety (HYV) seeds in India during the Green Revolution of the 1960s-1970s

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- How does the social environment within the village affect the <u>pace</u> of adoption? (Ultimately adopted everywhere). Do people in a village choose to free-ride off of others in the village when they make adoption decisions?

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- Theoretical “learning by doing” framework adapted from Jovanovic and Nyarko (1994)

- A “target input” model: farmers using HYV’s still need to learn how to apply complementary inputs (e.g., fertilizer, weeding, irrigation) to reap high returns. This could be location or even plot specific → need to experiment

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- Let the profit maximizing amount of fertilizer for plot i, farmer j, time t is $\theta_{ijt} = \theta^* + u_{ijt}$. If too much / too little is used, you make less profit. θ^* is the level that on average maximizes profit

The production technology and information restrictions are as follows: optimal or target-input use on each parcel of land i planted using the new seeds by farmer j in each period t, $\tilde{\theta}_{ijt}$, is given by

$$\tilde{\theta}_{ijt} = \theta^* + u_{ijt}, \tag{1}$$

where θ^* is the mean optimal use and u_{ijt} is an independently and identically distributed (i.i.d.) normal random variable with variance σ_u^2. We consider below the implications of contemporaneous spatial correlations in the target shocks. Farmers are assumed to know σ_u^2 and have priors over θ^* that are $N(\hat{\theta}_{j0}, \sigma^2_{\theta j0})$. Yield per parcel using traditional varieties is η_a, but yield per parcel using HYVs varies according to the suitability of land to HYVs and to input use. The (per parcel) yield from HYV seeds on the ith most HYV-suitable parcel for a farmer with A_j total parcels of land is given by

$$\eta_a + \eta_h - \eta_{ha}\frac{i}{A_j} \boxed{- (\theta_{ijt} - \tilde{\theta}_{ijt})^2}, \tag{2}$$

where θ_{ijt} denotes actual input use and η_{ha} reflects the loss associated with using less suitable land as more HYVs are used.

Given the stationarity in the distribution of the $\tilde{\theta}_{ijt}$'s, the time of information is irrelevant.[8] Assuming that farmer j has n neighbors, we may therefore use Bayesian updating to write

$$\sigma^2_{\theta_{jt}} = \frac{1}{\rho + \rho_o S_{jt} + \rho_v \overline{S}_{-jt}}, \tag{4}$$

where $\rho = 1/\sigma^2_{\theta 0}$ is the precision of the farmer's initial priors, $\rho_o = 1/\sigma^2_u$ is the precision of the information obtained from each parcel planted by j on his own farm, S_{jt} is the cumulative number of parcels planted by farmer j up to time t, and $\rho_v = n/(\sigma^2_u + \sigma^2_k)$ is the precision of the information obtained from an increase in $\overline{S}_{-jt}$, the average of the cumulative experience of neighboring farmers.

(2) Foster and Rosenzweig (1995, *JPE*)

- They derive optimal adoption of HYV varieties (in acreage, *H*) as a function of own and neighbors' past stock of adoption. This is a measure of the quality of information about using the technology. As past adoption goes up, we would expect future usage to also increase since the adoption risk falls

- The solution concept is Markov Perfect Equilibrium, so only stocks of past adoption matter. This effectively rules out community coordination to reach the optimal allocation. Should these be ruled out?

- If returns to experience with HYVs are decreasing, then → free-riding as neighbors' assets increase

(2) Foster and Rosenzweig (1995, *JPE*)

- Household panel data over three years (two first differences), 1968-1970

$$\Delta H_{jt} \approx \alpha_{ot+1} S_{jt+1} + \alpha_{vt+1} \overline{S}_{-jt+1} - \alpha_{ot} S_{jt} - \alpha_{vt} \overline{S}_{-jt} + \gamma_t \Delta t + \gamma_{ao} \Delta A_{jt} + \gamma_{av} \Delta \overline{A}_{-jt} + \Delta \epsilon_{hjt}, \quad (19)$$

ΔH_{jt} is the change in household HYV adoption

S_{jt} is the cumulative household parcels planted with HYVs by time t (why t+1 here?)

ΔA_{jt} is the change in household assets (farm equipment, livestock, irrigation assets)

(2) Foster and Rosenzweig (1995, *JPE*)

- Household panel data over three years (two first differences), 1968-1970
- Omitted variables are a concern: places where people have more experience with HYVs already may be places where returns to HYV are particularly high (and growing), or where people are particularly good at dealing with new technologies. Showing a correlation between past adoption and future changes in adoption is not enough

(2) Foster and Rosenzweig (1995, *JPE*)

- This paper's solution: IV for past individual and village HYV adoption using inherited HH assets (pre-1968), lagged HH profits, lagged village HYV use, lagged HH asset changes, and lagged village average assets

  -- Related to the Arellano and Bond (1991) approach

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- The social group is taken as the village

TABLE 3

DETERMINANTS OF FARM PROFITS FROM HYV USE (N = 450)

HYV EFFECTS	LINEAR APPROXIMATION: Instrumental Variables Fixed Effects (1)	LINEAR APPROXIMATION: Instrumental Variables Fixed Effects (2)	LINEAR APPROXIMATION: Constrained Instrumental Variables Fixed Effects (3)	STRUCTURAL ESTIMATES: Nonlinear Instrumental Variables Fixed Effects (4)
β_{st} (× 10^5)	.170 (2.13)	.293 (2.54)	.187 (1.88)	. . .
β_{st-1} (× 10^5)	.754 (2.47)	1.05 (2.18)	. . .	. . .
β_{it} (× 10^5)	. . .	.349 (2.16)	.341 (2.63)	. . .
β_{it-1} (× 10^5)	. . .	1.93 (2.64)	. . .	. . .
λ_{jt}	. . .		4.33 (10.6)	. . .
ρ_s (× 10^{-3})	. . .	. . .	. . .	1.29 (3.31)
ρ_v (× 10^{-3})	. . .	. . .	. . .	3.46 (1.33)
ρ (× 10^{-3})	. . .	. . .	. . .	.298 (6.23)
η_{ke} (× 10^4)	. . .	. . .	. . .	−.290 (3.24)
$\eta_k - \sigma_u^2$ (× 10^4)	. . .	. . .	. . .	.139 (.77)
η_k' (× 10^4)	−.206 (1.17)	−.545 (2.50)	−.344 (1.73)	. . .
η_{ke} (× 10^4)	.276 (1.22)	.434 (1.91)	.298 (1.34)	.610 (3.54)
Farm equipment	2.25 (2.98)	2.64 (2.59)	2.55 (2.68)	1.67 (2.73)
Farm animals	.641 (.57)	.813 (.68)	.543 (.49)	.189 (.207)
Irrigation assets	−1.06 (2.39)	−1.17 (2.41)	−.693 (1.39)	−1.40 (3.35)

TABLE 4

Determinants of HYV Use (N = 2,716)

	Instrumental Variables Fixed Effects (1)	Instrumental Variables Fixed Effects (2)	Constrained Instrumental Variables Fixed Effects (3)
α_{it}	.975	.791	.600
	(4.48)	(3.16)	(2.54)
α_{it-1}	.810	.691	...
	(2.60)	(2.39)	
α_{vt}	...	.715	1.04
		(1.60)	(1.70)
α_{vt-1}	...	.450	...
		(.66)	
λ_{kt}	...	...	.780
			(4.38)
Farm equipment: own ($\times 10^{-4}$)	4.26	3.11	2.90
	(2.05)	(2.08)	(2.08)
Farm animals: own ($\times 10^{-4}$)	1.81	.687	.695
	(4.57)	(2.58)	(2.53)
Irrigation assets: own ($\times 10^{-4}$)	.0681	.235	.240
	(.88)	(1.73)	(1.68)
Farm equipment: neighbor ($\times 10^{-4}$)	...	−.0878	−.0194
		(.34)	(.06)
Farm animals: neighbor ($\times 10^{-4}$)	...	−.995	−.948
		(2.08)	(1.85)
Irrigation assets: neighbor ($\times 10^{-4}$)	...	−2.12	−2.07
		(3.58)	(3.38)
Trend ($\times 10^{-2}$)	3.85	4.04	4.07
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(2) Foster and Rosenzweig (1995, *JPE*)

- Ethnographic evidence on how these effects are occurring would be useful. Are women talking to women? Men to men?

- Are people conscious of their free-riding choices? Do they understand that returns to experimentation are decreasing? What do they say when asked why they adopted more HYVs?

- This is an important case, but not one of failed adoption. Their simulations (Figure 2) suggest that the free-riding effects they emphasize are modest. Provides some support for public subsidies for early adopters

(3) Kremer and Miguel (2007)

- Follow-up to Miguel and Kremer (2004) on the impact of deworming treatment

- Recall the finding of large positive treatment externalities: individuals gain when others in their school or nearby (within 3 km, especially) receive deworming, by breaking the transmission cycle

- Social benefits of treatment are larger than private benefits. What are the implications of this for social learning about deworming drugs?

(3) Kremer and Miguel (2007)

- Attempts to deal with the main econometric issues in the social learning literature:

  (1) Exploit the randomized design of the project to deal with omitted variable bias. “Early adopters” and “later adopters” are determined in part by the experiment

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- Also explore “higher order” social links: links’ links

(3) Kremer and Miguel (2007)

- Theoretical framework: Bayesian learning framework incorporating multiple learning channels

  -- The key decision facing household *i* is whether or not to adopt deworming in period *t*, $T_{it} \in \{0,1\}$

- Individuals start out with a prior ϕ_{i0} and receive signals through their social network, from early treatment households, to create their posterior, ϕ_{it}

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- Private benefits are a function of the infection level, $h(\gamma_{it})$

  -- Utility benefits to imitating others are possible

- Time / financial costs of adoptions are $C > 0$

Let $\hat{\phi}_{it}$ denote the individual's beliefs in period t about drug effectiveness ϕ conditional on prior beliefs and any signals received, and let $T_{it} \in \{0, 1\}$ be an indicator variable for drug take-up in period t. Then the individual's expected private benefit from adoption can be expressed as

$$E\left[U(T_{it} = 1) - U(T_{it} = 0)\right] = \hat{\phi}_{it} h(\gamma_{it})\mu_i - C + \beta\omega_{it} \quad (1)$$

where U is individual utility from deworming, conditional on the treatment choices of other individuals, and ω_{it} is the share of social contacts who took up the drug in the previous period.

(3) Kremer and Miguel (2007)

- As individuals accumulate signals, their beliefs converge to actual drug effectiveness ϕ (as long as imitation effects are not sufficiently strong)

- If priors are “too pessimistic” ($\phi_0 < \phi$), then take-up rises over time. If priors are “too optimistic” ($\phi_0 > \phi$), then take-up falls over time. In our context, if households confuse social and private benefits, their priors may be systematically wrong

  -- Allow priors to differ as a function of education, X_i

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- Why not immediate convergence? "Frictions": probability $p < 1$ send signal in each period, signals move slowly

An additional signal can impact take-up behavior, so that $\left[\left(T_{it} \mid \text{Signal}\right) - \left(T_{it} \mid \text{No signal}\right)\right]$ is nonzero, by changing beliefs about ϕ (or similarly by reducing the cost of take-up C, as discussed below). If a Bayesian individual has N_{it}^{E} total signals from early treatment school links, both direct (first-order) and indirect (higher-order), she then weights her prior beliefs and signals received from social links such that the posterior belief on expected effectiveness becomes:

$$\hat{\phi}_{it} = \left[\left\{ \frac{\sigma_N^2}{\sigma_N^2 + \sigma_0^2} \right\} \cdot \phi_0(X_i) + \left(1 - \left\{ \frac{\sigma_N^2}{\sigma_N^2 + \sigma_0^2} \right\} \right) \cdot \phi_S \right] \tag{4}$$

where $\phi_0(X_i)$ is the mean of her prior distribution, ϕ_S is the sample average of signals received through the social network, and $\sigma_N^2 \equiv \sigma_\varepsilon^2 / N_{it}^{E}$ denotes the variance of the sample average. As individuals accumulate more signals through their social network, the variance of the sample average goes to zero, and the value of both the sample average and posterior beliefs approach the true expected effectiveness, ϕ.

The impact of early treatment links on the expected private benefits to adoption is thus

$$\frac{\partial E\left[U(T_{it}=1)-U(T_{it}=0)\right]}{\partial N_{it}^{E}} = \left[\frac{-\sigma_N^2\sigma_0^2}{\left(\sigma_N^2+\sigma_0^2\right)^2 N_{it}^{E}}\right]\cdot\left(\phi_0(X_i)-\phi_S\right)\cdot h\left(\gamma(\omega_{it},X_i)\right)\cdot\mu_i$$

$$-\frac{\partial C\left(N_{it}^{E}\right)}{\partial N_{it}^{E}}+\hat{\phi}_{it}\frac{\partial h}{\partial\gamma}\cdot\frac{\partial\gamma(\omega_{it},X_i)}{\partial\omega_{it}}\cdot\frac{\partial\omega_{it}}{\partial N_{it}^{E}}\mu_i+\beta\frac{\partial\omega_{it}}{\partial N_{it}^{E}} \qquad (5)$$

The first right-hand side term is the social effect from *information on drug effectiveness*, and can be positive or negative depending on the difference between priors and true private adoption benefits. The second term captures the social effect from *learning how to use the drugs* described above, and is always positive. The third term is the *infection social effect*, which should be negative because having more early treatment links could lead to a lower individual infection level (due to epidemiological externalities), which in turn reduces treatment benefits. The positive *imitation effect* is captured in the fourth term.

(3) Kremer and Miguel (2007)

- Data on 1700 parents (in Group 2 and Group 3 schools) collected in 2001, roughly 40 per school
- Detailed information on their social links: 10.2 total links per household on average, 2.8 who have children in deworming sample schools
- Information on take-up from school records
- Parent beliefs also captured in the surveys

(3) Kremer and Miguel (2007)

- Econometric identification relies on the randomized phase-in of sample schools into deworming: compare parents with a greater share of friends in Group 1 and Group 2 (early treatment) schools to those with more friends in Group 3 (not yet treated) schools

The cost-sharing indicator variable, $COST_j$, takes on a value of one for schools participating in the cost-sharing project, where the financial cost of treatment was higher. Z_{ij} is a vector of additional household socioeconomic characteristics (parents' education and asset ownership), demographic characteristics (respondent fertility), and other controls (respondent membership in community groups, and a Group 2 indicator) that may affect real or perceived deworming benefits and costs. Idiosyncratic disturbance terms are allowed to be correlated within each school as a result of common influences, such as headmaster efforts in promoting the program. Equation 6 presents the main probit specification:

$$\Pr(T_{ij} = 1) = \Phi\{N_{ij}^{E\,'} a + N_{ij}' b_1 + b_2 COST_j + Z_{ij}' b_3 + e_{ij}\} \qquad (6)$$

We include interaction terms between household characteristics and social links to estimate heterogeneous treatment effects, for example, as a function of respondent education, and also estimate effects of different types of social connections (e.g., links to relatives versus friends).

(3) Kremer and Miguel (2007)

- Econometric identification relies on the randomized phase-in of sample schools into deworming: compare parents with a greater share of friends in Group 1 and Group 2 (early treatment) schools to those with more friends in Group 3 (not yet treated) schools

- Validate that the experiment “worked”: those with more early treatment social links look similar to those with few such links (Table 2)

Table 3: Non-Experimental Social Effect Estimates (Groups 2 and 3)

Explanatory variables:	Dependent variable: Child took deworming drugs in 2001 (1)	(2)	(3)
Proportion deworming drug take-up in 2001, respondent's own school (not including respondent)	0.84^{***} (0.11)		
# Parent links with children in respondent's own school whose children received deworming		0.015 (0.011)	
# Parent links with children in early treatment schools whose children received deworming and had "good effects"			0.004 (0.021)
# Parent links with children in early treatment schools whose children received deworming and had "side effects"			-0.112 (0.082)
# Parent links with children in early treatment schools whose children received deworming and respondent does not know effects			0.006 (0.046)
# Parent links with children in early treatment schools whose children did not receive deworming			-0.007 (0.028)
# Parent links with children in early treatment schools, respondent does not know whether they received deworming			-0.013 (0.016)
Total social link controls, socio-economic controls	Yes	Yes	Yes
Number of observations (parents)	1678	886	886
Mean of dependent variable	0.61	0.56	0.56

Table 4: Experimental Social Effect Estimates (Groups 2 and 3)

	Dependent variable: Child took deworming drugs in 2001				
Explanatory variables:	(1)	(2)	(3)	(4)	(5)
# Parent links with children in early treatment schools (Groups 1 and 2, not own school)	-0.031**	-0.041**			-0.002
	(0.014)	(0.017)			(0.018)
# Parent links with children in early treatment schools * Group 2 school indicator		0.018			
		(0.029)			
Proportion direct (first-order) parent links with children in early treatment schools			-0.098**		
			(0.045)		
# Parent links with children in early treatment schools, with whom respondent speaks at least twice/week				-0.030**	
				(0.016)	
# Parent links with children in early treatment schools, with whom respondent speaks less than twice/week				-0.033	
				(0.033)	
# Parent links with children in Group 1, 2, or 3 schools, not own school, with whom respondent speaks at least twice/week				0.008	
				(0.012)	
# Parent links with children in Group 1, 2, or 3 schools, not own school, with whom respondent speaks less than twice/week				0.025	
				(0.028)	
# Parent links with children in early treatment schools * Respondent years of education					-0.0062*
					(0.0032)
# Parent links with children in Group 1, 2, or 3 schools, not own school	0.013	0.013	-0.006		-0.014
	(0.011)	(0.017)	(0.009)		(0.014)
# Parent links with children not in Group 1, 2, or 3 schools	-0.008	-0.008	-0.005	-0.008	-0.008
	(0.007)	(0.009)	(0.007)	(0.007)	(0.011)
# Parent links, total	0.019***	0.029***	0.021***	0.018***	0.013
	(0.005)	(0.007)	(0.007)	(0.005)	(0.008)
Respondent years of education	0.003	0.003	0.002	0.002	-0.016
	(0.003)	(0.003)	(0.004)	(0.003)	(0.012)

Table 5: First-order and Higher-order Social Effect Estimates (Groups 2 and 3)

	Dependent variable: Child took deworming drugs in 2001				
Explanatory variables:	(1)	(2)	(3)	(4)	(5)
# Parent links with children in early treatment schools (Groups 1 and 2, not own school)	-0.031**		-0.044***		-0.037**
	(0.014)		(0.015)		(0.015)
# Parent links with children in Group 1, 2, or 3 schools, not own school	0.013		0.020		0.02
	(0.011)		(0.015)		(0.015)
Proportion direct (first-order) parent links with children in early treatment schools				-0.14***	
				(0.05)	
Second-order exposure to early treatment schools (Groups 1 and 2, not own school), parent links		-0.035***	-0.047***		-0.048***
		(0.013)	(0.013)		(0.014)
Second-order exposure to Group 1, 2 or 3 schools (not own school), parent links		0.025**	0.032**		0.033***
		(0.012)	(0.012)		(0.012)
Proportion second-order parent links with children in early treatment schools				-0.23***	
				(0.09)	
Third-order exposure to early treatment schools (Groups 1 and 2, not own school), parent links					-0.014
					(0.012)
Third-order exposure to Group 1, 2 or 3 schools (not own school), parent links					0.008
					(0.01)
Total social link controls, socio-economic controls	Yes	Yes	Yes	Yes	Yes
Number of observations (parents)	1678	1678	1678	1173	1678
Mean of dependent variable	0.61	0.61	0.61	0.61	0.61

Table 6: Effects on Deworming Attitudes and Knowledge

Dependent variable:	Estimate on # Parent links with children in early treatment schools [Experimental]	Estimate on # Parent links with children in early treatment schools whose children received deworming [Non-experimental]	Estimate on # Parent links with children in early treatment schools with whom respondent spoke about deworming [Non-experimental]	Mean dep. var.
Panel A: Attitudes				
1) Parent thinks deworming drugs "not effective"	0.017^{**} (0.007)	0.013 (0.008)	0.009^{**} (0.004)	0.12
2) Parent thinks deworming drugs "very effective"	-0.007 (0.010)	0.026^{**} (0.013)	0.040^{***} (0.007)	0.43
3) Parent thinks deworming drugs have "side effects"	0.000 (0.003)	-0.001 (0.003)	0.003^{*} (0.002)	0.04
4) Parent thinks worms and schisto. "very bad" for child health	-0.001 (0.006)	-0.004 (0.006)	-0.006^{*} (0.003)	0.92
Panel B: Knowledge				
5) Parent "knows about ICS deworming program"	0.004 (0.011)	0.050^{***} (0.014)	0.055^{***} (0.011)	0.70
6) Parent "knows about the effects of worms and schistosomiasis"	-0.001 (0.013)	0.045^{***} (0.013)	0.039^{***} (0.009)	0.68
7) Number of infection symptoms parents able to name (0-10)	-0.006 (0.005)	0.018^{**} (0.008)	0.010^{**} (0.005)	1.8
8) Parent able to name "fatigue" as symptom of infection	-0.004 (0.010)	0.028^{***} (0.009)	0.021^{***} (0.006)	0.20
9) Parent able to name "anemia" as symptom of infection	0.005 (0.009)	-0.003 (0.011)	0.010^{**} (0.005)	0.22
10) Parent able to name "weight loss" as symptom of infection	0.002 (0.006)	0.004 (0.005)	-0.001 (0.004)	0.06

(3) Kremer and Miguel (2007)

- Cost-sharing results (Table 7) also shed light on the low valuation households place on deworming

- The externality explanation may be more general than just for deworming, and may apply to other infectious and parasitic diseases with treatment externalities. If good treatments for infectious diseases do not spread on their own, since social benefits are larger than private benefits, then subsidies may be necessary for high take-up rates → a potential rationale for large public subsidies for infectious and parasitic disease treatments in poor countries

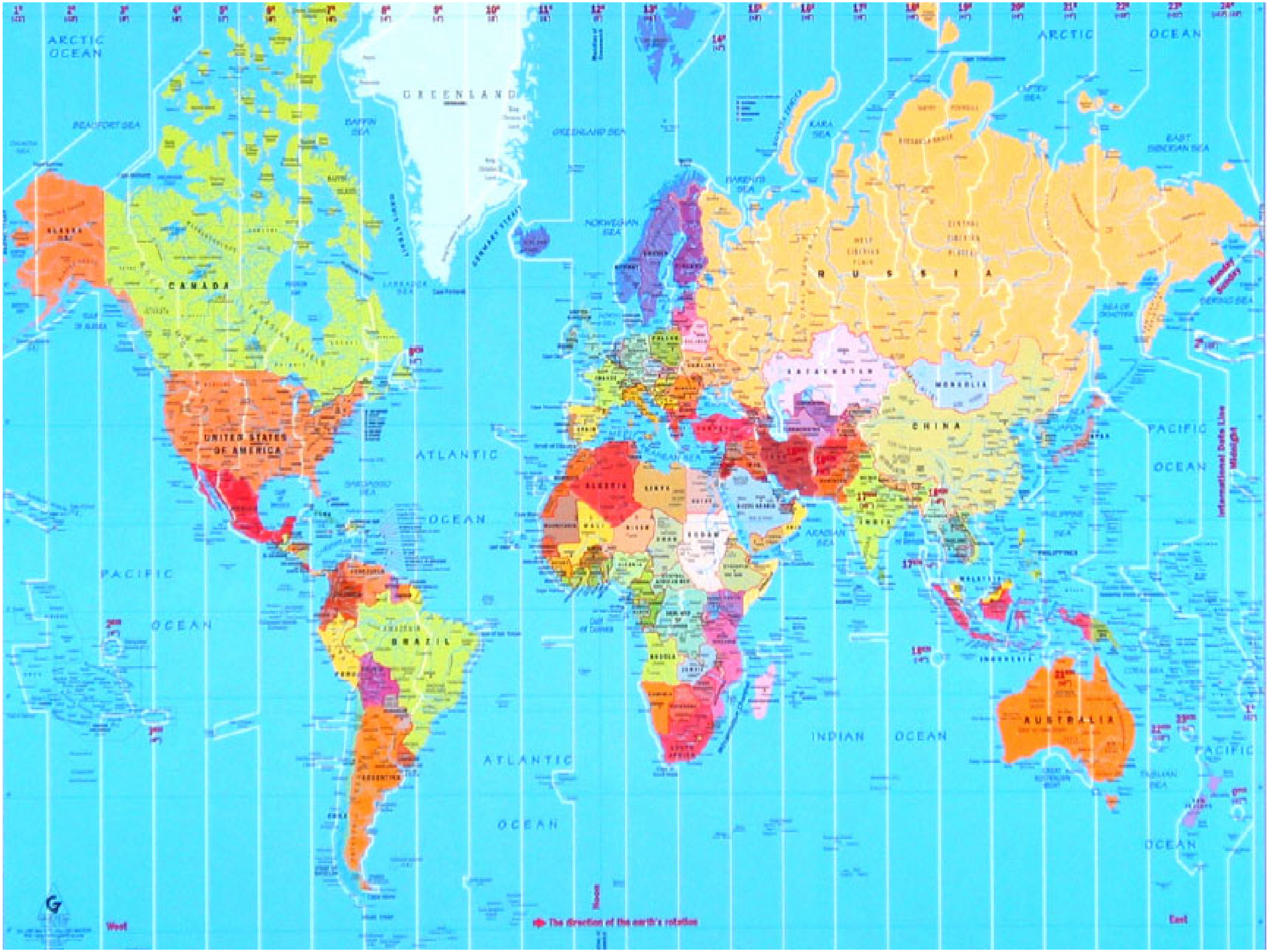
Whiteboard #1

Whiteboard #2

Whiteboard #3

Whiteboard #4

Whiteboard #5


ARCTIC OCEAN
GREENLAND
CANADA
UNITED STATES OF AMERICA
BRAZIL
ATLANTIC OCEAN
PACIFIC OCEAN
INDIAN OCEAN
RUSSIA
CHINA
MONGOLIA
KAZAKHSTAN
INDIA
AUSTRALIA
ALGERIA
LIBYA
SUDAN
NIGER
SAUDI ARABIA
INDONESIA
ARGENTINA
BEAUFORT SEA
BAFFIN SEA
GREENLAND SEA
NORWEGIAN SEA
BARENTS SEA
KARA SEA
LAPTEV SEA
EAST SIBERIAN SEA
ARABIAN SEA
TASMAN SEA
International Date Line
Midnight
West
East
The direction of the earth's rotation