Economics 270B
Ph.D. Development Economics

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Lecture 7 – March 16, 2015

I. Overview of International Economic Development
Lecture 1: Understanding economic growth and development (1/26)
Lecture 1B: Persistence of historical institutions and shocks (read during holiday week of 2/16)

Lecture 2: The Psychology of Poverty (2/2)

II. Human Capital in Economic Development
Lectures 3-4: Education (2/9, 2/23)
Lectures 5-7: Health and nutrition (3/2, 3/9, 3/16)

III. Political economy
Lectures 8-9: Democracy, Corruption and Development (3/30, 4/6) (guest lectures by Prof. Fred Finan)

Lecture 10: Ethnic and Social Divisions (4/13)
Lectures 11-12: The Political Economy of Conflict (4/20, 4/27)

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- Prerequisites: Graduate economic theory, econometrics
- Grading:
  Four referee reports – 40%
  → Report #4 on Fetzer paper due today (3/16)

  Two problem sets – 20%
  Research proposal – 30%
  Class participation – 10%
  No final exam
- All readings are available on bCourses

Any questions?

Lecture 7 outline

(1) The demand for health and life in poor countries (survey article Greenstone and Jack 2015)

(2) Gong (2015) on HIV/AIDS and sexual behavior

(3) Dupas (2014) on temporary subsidies and the adoption of health products

(1) Health choices in poor countries

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- Many development observers believe the take-up of useful health behaviors and technologies is **surprisingly low** in less developed countries

- E.g., the continued spread of HIV in Africa, slow adoption of better purification water technologies in South Asia, low-pollution cook stoves, etc.

  -- Similar claims are often made about other sectors in development, most importantly in agriculture

- Deworming and HIV prevention are concrete examples of "lower than expected" demand for useful health practices, with important implications for economics and policy

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- Historically lots of slogans – but limited evidence
- **Advocates:**
  - The poor can (and do) pay at least some fees
  - Fees are vital to sustainability, motivating providers
  - Charging may screen out low valuation consumers
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  - Charging may screen out low valuation consumers
  - Sunk cost effects ("ownership")
- **Critics:** negative impacts on access and use
- Recent RCT's have provided lessons on the impact of price on take-up of health services and products. Implications for the value people place on health and life (Dupas 2011 *Annual Review of Economics* survey)

(1) Valuing life and health

- Public policy decisions on the environment, health, and transportation all require estimates of a society's willingness to pay to reduce the mortality risks associated with alternative policies (Greenstone and Jack 2015)
  - For example, how much should be spent on road safety in order to save N lives (in expectation)?

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- Public policy decisions on the environment, health, and transportation all require estimates of a society's willingness to pay to reduce the mortality risks associated with alternative policies (Greenstone and Jack 2013)
  - For example, how much should be spent on road safety in order to save N lives (in expectation)?
- When individuals face options – each implying different degrees of mortality risk and cost – one can use the information contained in actual choices to estimate individual willingness to pay for reduced fatality risk.

→ A measure of the **Value of a Statistical Life** (VSL)

(1) Valuing health and life

- How do people make health spending choices (including re: user fees), and how does it differ from other choices?
- Imagine the following thought experiment. You have the option of reducing your risk of dying (mortality) by one percentage point over the next 30 years (say), but need to pay something up front to do so. How much are you **willing to pay** (WTP) to increase your life span?

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- Calculations like this allow us to compute a **value of a statistical life** (VSL), which is the monetary value (ΔP) per unit of reduced mortality risk (ΔR): VSL $\equiv$ -(ΔP/ΔR)

  -- Here if you are willing to pay US$1,000, **a lower bound** on the estimated VSL is –($1000/(-0.01)) = $100,000.

(1) Valuing health and life

- Researchers have taken advantage of some real world situations ("natural experiments") that approximate this type of choice to estimate VSL

- Ex. 1: workers that have riskier jobs in terms of accident and mortality risk (e.g., climbing utility poles, working near large gears / machinery, etc.) are typically paid more than other workers, and this wage "premium" can be interpreted as compensation for mortality risk

  -- U.S. studies typically estimate valuations **US$1-9 million**

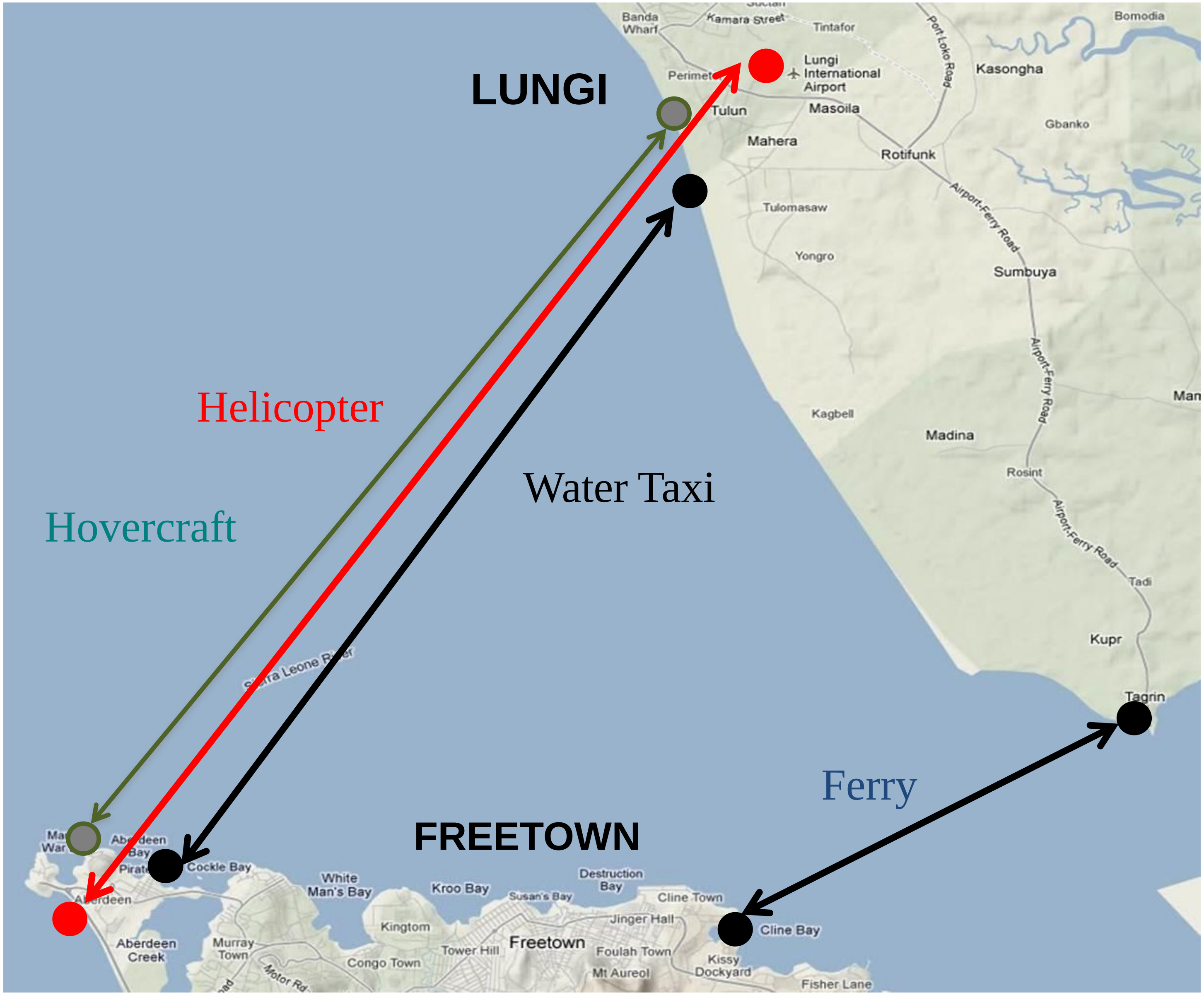
(1) Valuing health and life

- Ex. 2: Individuals' willingness to take on extra mortality risk in exchange for reduced travels costs in a transportation situation can also be used to compute a revealed preference estimate of the VSL

  -- Leon and Miguel (2015) examine an unusual situation in Sierra Leone, when travellers from Lungi International Airport and Freetown must cross an estuary roughly twice the distance across the Bay Bridge.

  -- The four choices – (i) ferry, (ii) water taxi, (iii) hovercraft, (iv) helicopter – all entail non-trivial accident risk and have different ticket costs and travel times (opportunity cost)

Map of Lungi Airport and Freetown, Sierra Leone



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  -- These "elite" African travellers have an implied average VSL of **US$577,000**, and foreign travellers US$924,000

(1) Valuing health and life

- Ex. 3: Health investments in poor countries can be viewed this way. Parents' willingness to purchase a mosquito net (or water treatment technology) that reduces infant mortality by 1% (say) at a certain price \$P delivers a **lower bound** on the value of a child life of –(\$P/(-0.01)) = \$100P

  -- Individuals with a value of life V, such that V > \$100P will be willing to pay for this treatment

  -- In rural Kenya, Kremer et al (2011) examine the willingness to pay for improved water quality (by walking longer distances to cleaner sources), and estimate a VSL of only US\$1,000.

  -- Like Leon and Miguel (2015), use discrete choice mixed logit models that allow for heterogeneous valuations.

(1) Valuing health and life

- How should we interpret VSL estimates?
- They are **not** meant to be some abstract moral valuation on human existence. Rather it is a **revealed preference** measure of individual willingness **and ability** to pay for a longer life. Factors that come into play include:

(1) Valuing health and life

- How should we interpret VSL estimates?
- They are **not** meant to be some abstract moral valuation on human existence. Rather it is a **revealed preference** measure of individual willingness **and ability** to pay for a longer life. Factors that come into play include:

  -- Information: people may not fully understand the link between a treatment (or job, or behavior) and mortality risk

  -- Income: individuals with lower income will simply have less money to spend on these investments

  -- Liquidity constraints: even if future income is expected to rise, current cash and borrowing may be constrained

- Other factors, limitations, and caveats?

(1) Valuing health and life

- Some existing estimates suggest that the VSL increases “more than linearly” with per capita income. I.e., per capita income is roughly 60x higher in the U.S. than in Kenya (US$50,000 versus $800) but the estimated VSL is perhaps 3,000x higher ($3 million versus $1,000).

- Why? No definitive answers but a suggestive one:

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- Why? No definitive answers but a suggestive one:

  -- Richer people may get more out of investing in health than poor people, if there is **decreasing marginal utility** to consumption of "stuff" (e.g., food, cars) but **constant marginal utility** to being alive (Hall and Jones 2006, *QJE*)

  -- Since more of the disease burden in poor countries is due to infectious diseases, the degree of externalities may also affect observed WTP for health investments

(2) HIV information and risky sex (Gong 2015)

- Another leading puzzle is continued high risk sexual behavior in Sub-Saharan Africa in the midst of the HIV/AIDS epidemic

- It has been difficult to make progress due to:

(1) difficulty objectively measuring risky sexual behavior,

(2) lack of exogenous variation in important factors (i.e., information),

(3) a disconnect between the behavioral models developed by social scientists and the research designs employed by health researchers.

(2) HIV information and risky sex (Gong 2015)

- Gong (2015) makes progress on all three, and is a nice example of the integration of theory, experimental data

- Medium sized samples of self-selected individuals (interested in HIV tests) in both Nairobi, Kenya and Dar es Salaam, Tanzania, in the late 1990s

- Randomized into HIV testing arm (treatment), or control

(2) HIV information and risky sex (Gong 2015)

- Simple model of risky sexual behavior
- Key question: how do individuals respond to learning their own HIV status?

- Leading theoretical channels:

(1) “nothing to lose”: if you are already infected, choose more risky sex;

(2) “altruism effect”: if you care about your partner(s), choose less risky sex.

- Behavioral response to more information about one’s infection status is ambiguous → empirical question

An individual chooses a level of risky sexual behavior j which generates $u(j)$ utility. While risky sex can take multiple forms, in this model j represents the number of sexual partners. The level of risky sexual behavior is a function of beliefs of HIV infection, which I denote as $\pi \in [0,1]$. Those who believe they are at higher risk for HIV have higher values of π, where $\pi = 1$ for those who are certain they are HIV-positive and $\pi = 0$ for those who are certain they are HIV-negative. Each time an individual partners sexual with someone, they face a probability of HIV-infection $\lambda(\beta, W)$ which is a function of β (HIV transmission rate) and W (prevalence of HIV).[11] [12] Finally, c is the disutility that comes from knowing that you are HIV-positive. I assume $u(j)$ is increasing in j and concave. Individuals then must choose j that maximizes the following utility function:

$$U(j) = u(j) - [\pi + (1-\pi)j\lambda(\beta, W)]c$$

The first-order condition equates the marginal benefit of risky sexual behavior with the marginal cost:

j^*

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Thought experiments on beliefs: $\pi = 0$; $\pi = 1$

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Thought experiment on anti-retroviral treatment: *c* falls; λ falls

$$u_j = (1-\pi)\lambda(\beta, W)c$$

I now introduce altruism to the model which takes the form of a discount to the utility one receives from risky sex:

$$U(j) = u(j)A(\pi) - [\pi + (1-\pi)j\lambda(\beta, W)]c$$

where $A(\pi) \in [0,1]$ is a function of beliefs of HIV infection and serves to discount the marginal benefit of risky sex. I assume that $A_\pi < 0$ or that as beliefs increase, a greater discount is applied to the utility of risky sex.

How does risky sexual behavior respond to HIV testing? We can think of HIV tests as shocks to beliefs (π), where someone surprised by an HIV-positive (HIV-negative) test has $\Delta\pi > 0$ ($\Delta\pi < 0$). When an HIV test confirms an individual's priors , beliefs are unchanged ($\Delta\pi = 0$).

The comparative statics show how behavior (j) responds to a change in beliefs (π):

Application of the envelop theorem:

$$\frac{\partial j}{\partial \pi} = -\left(\frac{u_j A_\pi + \lambda(\beta, W)c}{u_{jj}A(\pi)}\right) \tag{1}$$

Since by concavity, $u''(j) < 0$, and given a non-zero HIV transmission rate ($\lambda(\beta, W) > 0$), the sign of $\frac{\partial j}{\partial \pi}$ depends on $u'(j)A_\pi + \lambda(B, W)c$. When $|A_\pi|$

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(2) HIV information and risky sex (Gong 2015)

- Main hypothesis is that the impact of information will differ depending on both (i) prior beliefs about the likelihood of infection (π_0), and (ii) the actual realization of the HIV test ($\pi = 0$ or $\pi = 1$).

- Those who are “surprised” ($\Delta\pi \neq 0$) should react more than those whose priors line up with their infection status, but the sign of the effect is ambiguous because of the potentially offsetting effects.

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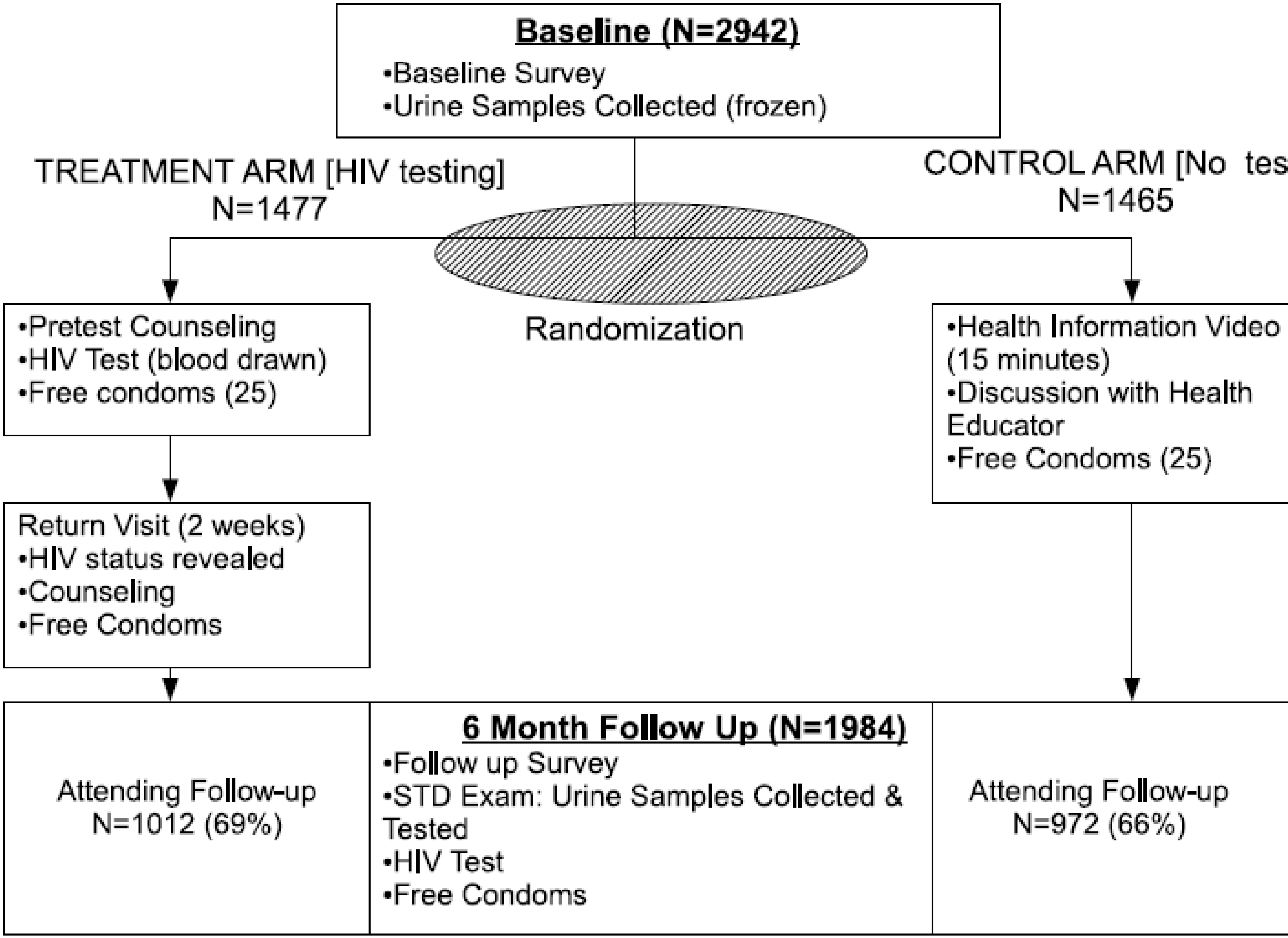
- Reality may be more complicated, i.e., baseline beliefs could be affected by perceived local prevalence *W* (i.e., $\pi_0(W)$), as could the degree of altruism, $A(\pi, W)$

Figure A.I: Study Design



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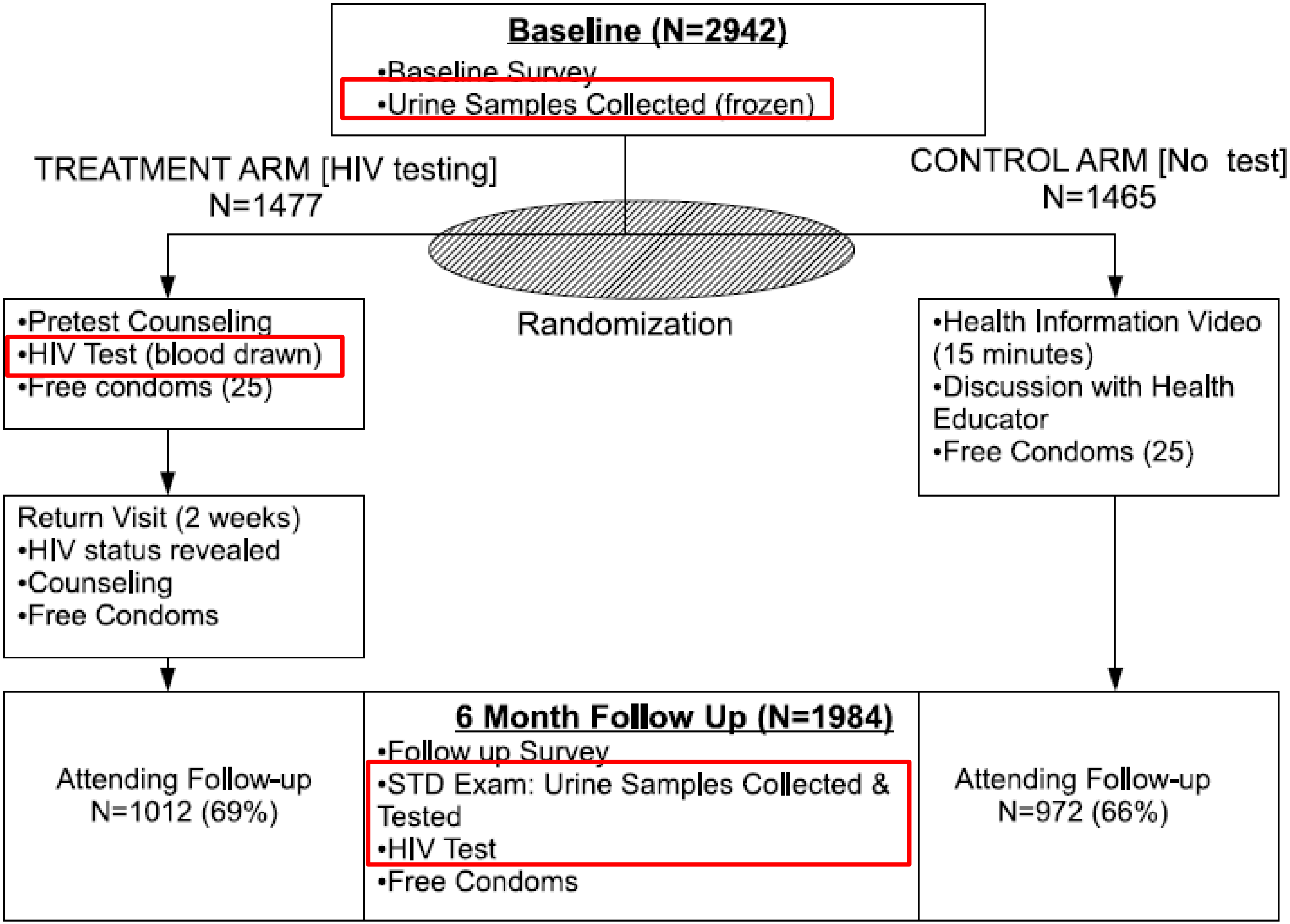

$|\Delta\pi| > 0$

Four Groups for Analysis: Effect of Testing in Each Group		
	HIV-Negative	HIV-Positive
Low Prior Beliefs	Tests have little effect on beliefs or behavior	Tests increase beliefs => Change in behavior
High Prior Beliefs	Tests decrease beliefs => Change in behavior	Tests have little effect on beliefs or behavior

The estimating equation is a linear probability model:

$$
\begin{aligned}
STI_{ij} \;=\;& \alpha + \beta_1 Test_i + \beta_2 High\,Priors_i + \beta_3 HIV_i + \beta_4 Couple_i \\
&+\beta_5(Test_i \times High\,Priors_i) + \beta_6(Test_i \times HIV_i) \qquad (2)\\
&+\beta_7(Test_i \times High\,Priors_i \times HIV_i) + I_i'\omega_1 + X_i'\delta_1 + \gamma_j + u_{ij}
\end{aligned}
$$

where $STI_{ij} = 1$ if individual i in country j contracts an STI during the study, $Test_i$ indicates assignment into the HIV testing arm, $High\,Priors_i$ indicates if the individual has high prior beliefs, $HIV_i = 1$ for those who are HIV-positive, and $Couple_i$ indicates if the individual enrolled in the study with his/her partner. The vector I_i includes all the interactions of $Test_i$, $High\,Priors_i$, HIV_i, $Couple_i$ that are not explicitly specified, X_i' is a vector of individual level characteristics, and γ_j is a country fixed effect.

Using the predictions from the previous table, we should expect $\beta_1 = 0$ (low priors receiving HIV- test), $\beta_1 + \beta_6 \neq 0$ (low priors receiving HIV+ test), $\beta_1 + \beta_5 \neq 0$ (high priors receiving HIV- test), and $\beta_1 + \beta_5 + \beta_6 + \beta_7 = 0$ (high priors receiving HIV+ test).

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(2) HIV information and risky sex (Gong 2015)

- Evidence that those with high perceived risk of infection but a negative HIV test become **less** likely to have unsafe sex (i.e., fewer actual STI infections) and those with low perceived risk of infection but a positive HIV test become **more** likely to have unsafe sex

- On net, the "nothing to lose" effect dominates empirically → suggestive evidence that more information could lead to more risky sex among some groups.

- Heterogeneity: no strong gender differences but those who came to the clinic as a couple show no response to the tests (arguably due to greater altruism?)

Table III: STI Incidence (Risky Sexual Behavior) at Follow Up

		Sample N	Control Mean (1)	Test Mean (2)	Test-Control Differences (3)	p-value (4)
Panel A:						
(1)	Overall	1961	0.044	0.036	-0.008	0.36
Panel B: Condition on HIV Status						
(2)	HIV-Negative	1589	0.039	0.025	-0.014	0.11
(3)	HIV-Positive	372	0.067	0.083	0.017	0.54
Panel C: Conditioning on Status and Priors						
HIV-Negative						
(4)	Low Priors	902	0.024	0.025	0.000	0.97
$\boxed{(5)}$	High Priors	687	0.059	0.025	-0.034	0.02
HIV-Positive						
$\boxed{(6)}$	Low Priors	188	0.011	0.085	0.074	0.02
(7)	High Priors	184	0.128	0.082	-0.046	0.31

Table IV: Effect of HIV Testing on STI Incidence (Risky Sexual Behavior)
Dependent Variable: STI Incidence (mean = .039)

	(1)	(2)	(3)
(1) Test	-.009	.002	-.001
	(.009)	(.013)	(.013)
(2) High Prior Beliefs	.023	.056	.053
	(.009)**	(.019)***	(.020)***
(3) HIV+	.042	-.010	-.010
	(.014)***	(.013)	(.014)
(4) High Prior X HIV		.046	.036
		(.043)	(.044)
(5) Test X High Prior		-.051	-.048
		(.024)**	(.024)**
(6) Test X HIV		.103	.096
		(.042)**	(.043)**
(7) Test X High Prior X HIV		-.096	-.094
		(.059)	(.058)
Interactions	No	Yes	Yes
Controls	No	No	Yes
Obs.	1961	1961	1882
R^2	.013	.029	.054
Linear Combinations: Effect of HIV Tests by Prior Beliefs			
HIV– test on low prior group			
(8) Test		0.002	-0.001
		(0.013)	(0.014)
HIV+ test on low prior group			
(9) Test+(Test X HIV+)		0.105	0.095
		(0.041)***	(0.041)**
HIV– test on high prior group			
(10) Test+(Test X High)		-0.05	-0.049
		(0.02)**	(0.021)**
HIV+ test on high prior group			
(11) Test+(Test X HIV+)+(Test X High) +(Test X High X HIV+)		-0.043	-0.047
		(0.047)	(0.046)

Table VII: Effects of HIV Testing Conditioning on Relationship/Testing Status

	Relationship Status		Testing As	
	Single	Married	Individual	Couple
	(1)	(2)	(3)	(4)
Linear Combinations: Effect of HIV Tests by Prior Beliefs				
HIV- test on Low Prior Group				
(1) Test	0.007	-0.005	-0.007	0.010
	(0.017)	(0.020)	(0.013)	(0.020)
HIV+ test on Low Prior Group				
(2) Test+(Test X HIV)	0.084	0.063	0.122	-0.032
	(0.047)*	(0.074)	(0.044)***	(0.037)
HIV- test on High Prior Group				
(3) Test+(Test X High)	-0.051	-0.058	-0.044	-0.017
	(0.025)**	(0.038)	(0.021)**	(0.017)
HIV+ test on High Prior Group				
(4) Test+(Test X HIV)+(Test X High)	-0.028	-0.073	-0.075	0.009
+(Test X High X HIV)	(0.053)	(0.083)	(0.049)	(0.093)
Obs.	1118	764	1253	629

(2) HIV information and risky sex (Gong 2015)

- Self-reported sexual behavior does **not** respond the same as the actual STI results – and in some cases responses go in the opposite direction! Presumably due to social desirability bias.
- Especially worrisome for those with HIV+ tests

- (Are sexual behavior reports at all useful?)

Table VI: Effect of HIV Testing on Self Reported Sexual Behavior

Dependent Variable	STI Incidence (1)	Sexually Active (2)	Number of Partners (3)	Unprotected Sex with NPP (4)
Panel A: Overall Sample (N=1961)				
(1) Test	-0.012	-0.008	-0.171	-0.080***
	(0.011)	(0.025)	(0.159)	(0.023)
Mean Dep Var	0.044	0.784	1.227	0.218
Panel B: By HIV Status				
HIV- Sample (N=1589)				
(2) HIV- Test	-0.022*	0.021	-0.121	-0.069***
	(0.012)	(0.027)	(0.131)	(0.026)
Mean Dep Var	0.039	0.784	1.161	0.220
HIV+ Sample (N=372)				
(3) HIV+ Test	0.031	-0.126**	-0.368	-0.129***
	(0.033)	(0.058)	(0.611)	(0.047)
Mean Dep Var	0.067	0.783	1.511	0.211
Panel C: By HIV Status and Priors				
HIV+ and Low Prior Sample (N=188)				
(4) HIV+ Test	0.131***	-0.155*	-0.352**	-0.172***
	(0.044)	(0.082)	(0.159)	(0.064)
Mean Dep Var	0.011	0.787	1.106	0.213
HIV- and High Prior Sample (N=687)				
(5) HIV- Test	-0.043**	-0.029	0.035	-0.083**
	(0.020)	(0.038)	(0.120)	(0.041)
Mean Dep Var	0.059	0.820	1.183	0.280

(2) HIV information and risky sex (Gong 2015)

- Why do results differ from previous studies?

- Original *Lancet* article (Coates et al. 2000)
- Focus on pooled impacts, **miss heterogeneity** in beliefs
- Also fail to condition on baseline infection status, making invalid comparisons between HIV+ and HIV- people

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- Thornton (2008), de Paula et al (2010), and others all from large Malawi HIV/STI study (MDICP)
- Malawi is a rural sample (vs. large cities in Gong 2015)
- **Self-reported** sexual behavior outcomes, no biomarkers

(2) HIV information and risky sex (Gong 2015)

- Simulation results, based on epidemiological models
- Key point: under assumptions (about unprotected sex acts per partner, infectivity), translate increased infection prevalence to the change in the number of partners
- With this relationship established, one can simulate the implications for the broader "spread" of the virus in a population (with Kenya, Mozambique, Zambia DHS data)

- Main result: more testing increases the spread of the virus in some cases (e.g., Mozambique), not others, depending on distribution of infection, priors
- Possible solution is so-called **"test and treat"** policy, since treatment greatly reduces transmission.

(3) Dupas (2014) on subsidies and take-up

(3) Dupas (2014) on subsidies and take-up

- Related to earlier discussion on the impact of temporary subsidies for deworming on future take-up: could subsidies reduce later adoption by either **dampening “ownership”** for the good (development practitioners) or by **“anchoring” consumers at the lower price** (behavioral economics theory of reference dependence)
- Alternatively, temporary subsidies could boost later take-up by **promoting individual learning** about the product, and possibly generating **positive social learning** externalities

- Dupas (2014) examines the case of subsidies for anti-malarial bednets in Kenya

(3) Dupas (2014) on subsidies and take-up

- 4 communities, N=599 households with 2 years of data
- Experimental variation in **price subsidies** for a new type of anti-malarial bednet (not previously locally available), from full subsidy (zero cost) to $3.80 in Year 1
- In Year 2, all households face a price of $2.30 for an additional bednet

- Is take-up in Year 2 lower in the higher subsidy households? Many reasons to think it might be: they may be more likely to already have one (if demand curves are downward sloping), they may not value it as much (the "ownership" story told by practitioners), etc.

(3) Dupas (2014) on subsidies and take-up

- Main findings:
- The **demand curve** is strongly downward sloping in Year 1, as expected (and as in Kremer and Miguel 2007)
- Conditional on take-up, those who paid less for the nets are if anything slightly **more likely** to use them (rather than less likely)
- Despite being much more likely to already have a net, those who received higher subsidies in Year 1 are **more likely** to purchase another in Year 2, suggesting they learned about its benefits and value it more
- Follow the Miguel and Kremer (2004) spillover estimation approach, and show take-up social effects are positive in Year 1, but surprisingly negative in Year 2

(3) Dupas (2014) on subsidies and take-up

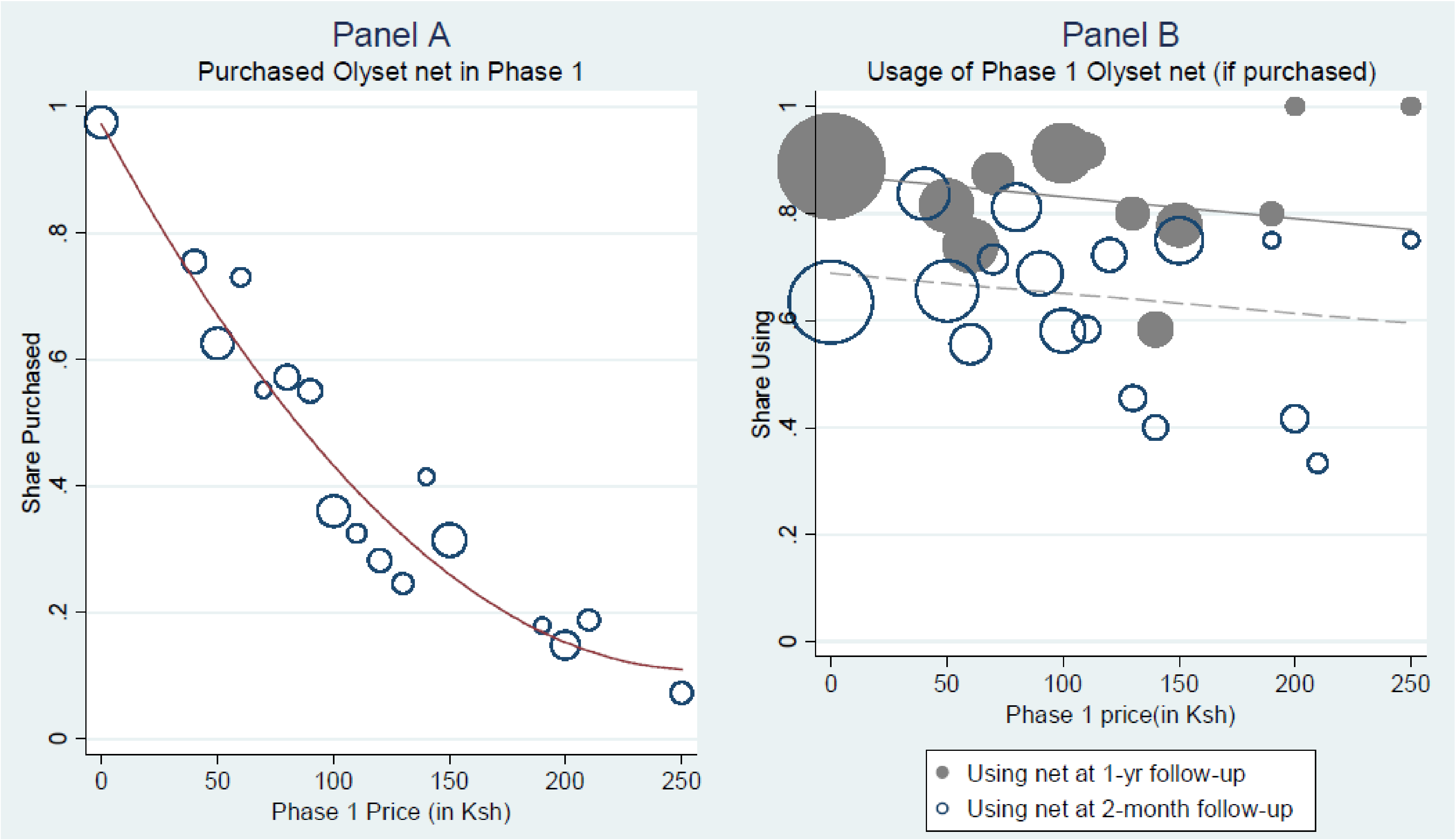

Figure 1

(3) Dupas (2014) on subsidies and take-up

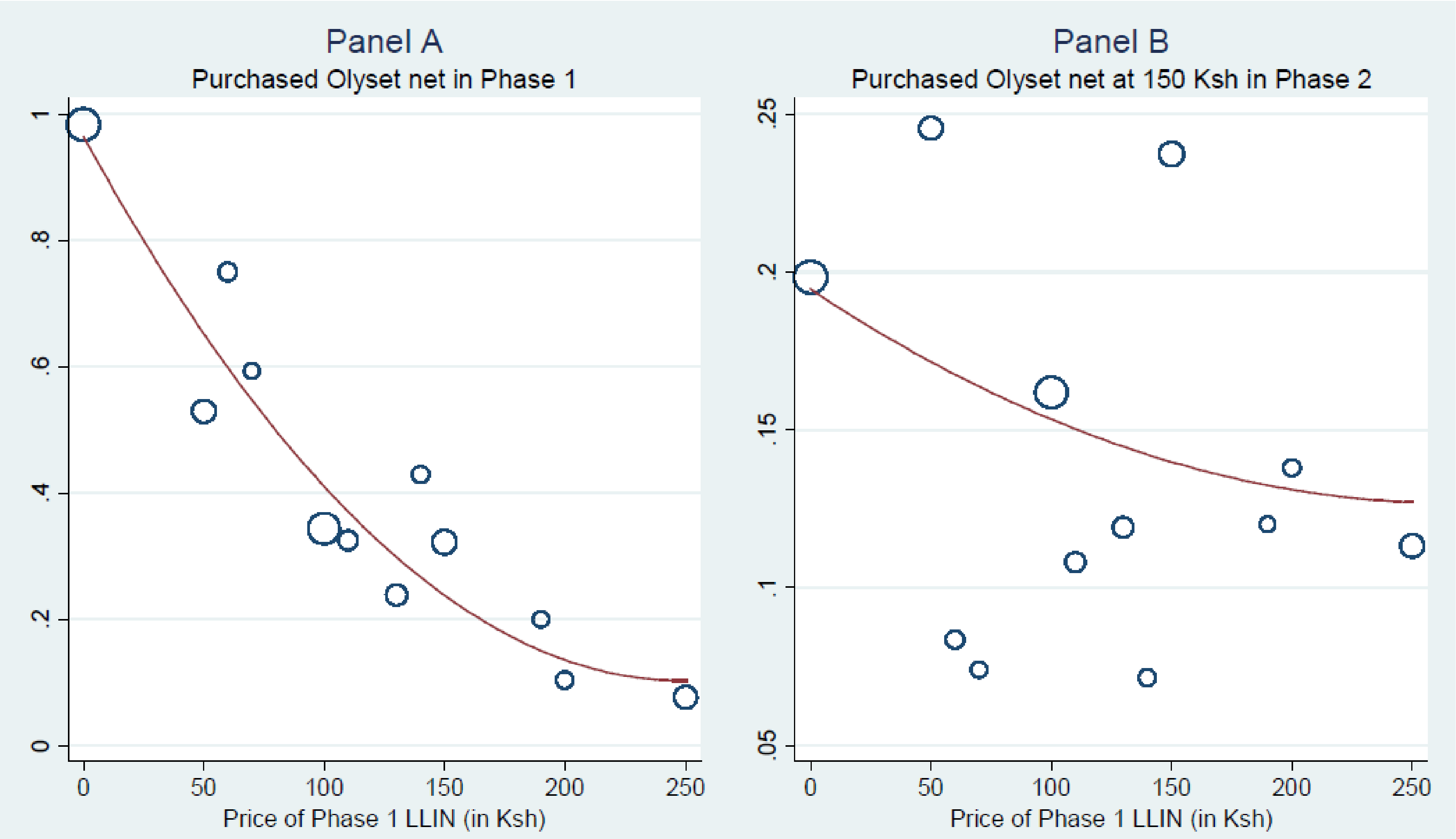

Figure 2

(3) Dupas (2014) on subsidies and take-up

Table 2. Experimental results

	(1)	(2)	(3)
	Purchased Olyset net in Phase 1	Purchased and Used Olyset net in Phase 1[a]	Purchased Olyset at 150 Ksh in Phase 2
Phase 1 Price ≤ 50 Ksh (High Subsidy)	0.387	0.281	0.068
	(0.034)***	(0.033)***	(0.040)*
	[0.034]***	[0.033]***	[0.04]*
Density of Phase 1 High Subsidy recipients within 500 meter radius	0.223	0.168	-0.183
	(0.092)**	(0.090)*	(0.099)*
	[0.083]***	[0.088]*	[0.119]
Area Fixed effects	Yes	Yes	Yes
Observations	1094	1094	584
Mean of Dependent Variable	0.458	0.321	0.158
Mean of Dependent Variable in non-"High Subsidy" group	0.341	0.233	0.137

Table 2

(3) Dupas (2014) on subsidies and take-up

- Structural modeling exercise using maximum likelihood (discrete choice model, logistic disturbance terms)

- Useful idea, but **many strong assumptions** are needed to achieve identification of model parameters, including no learning about health “quality” /impact of the product across households, no experimentation to learn about quality, and no anticipation of spillovers, etc.

The Hobo-Dyer Equal Area Projection
CANADA
U.S.A.
MEXICO
PACIFIC OCEAN
ATLANTIC OCEAN
COLOMBIA
BRAZIL
BOLIVIA
PERU
ARGENTINA
RUSSIA
KAZAKSTAN
MONGOLIA
CHINA
JAPAN
TURKEY
IRAN
IRAQ
INDIA
ALGERIA
LIBYA
EGYPT
SAUDI ARABIA
SUDAN
MALI
NIGER
CHAD
NIGERIA
ETHIOPIA
SOMALIA
ANGOLA
ZAMBIA
SOUTH AFRICA
INDIAN OCEAN
INDONESIA
PAPUA NEW GUINEA
PHILIPPINES
AUSTRALIA
NEW ZEALAND
KIRIBATI
SOUTHERN OCEAN
ANTARCTICA

Next week

- For next week, enjoy spring break!
- For the next two lectures, Fred Finan will present the material for Lectures 8-9, “Democracy, corruption and development”.
- The first problem set will be due the following our return from spring break (April 6th).