

# **REACHING THE NOVICE OR NUDGING THE EXPERT? NETWORKS, INFORMATION, AND EXPERIMENTAL RETURNS TO MIGRATION**

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NEUDC

## THANKS AND DISCLAIMERS



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## STARK URBAN-RURAL GAP IN KENYA



Pictures show a rural Kenyan home and Nairobi, the capital city of Kenya. Source: Jocelyn Diaz (left) and Catalin Marin (right).

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  - because experimenting is costly, migrant relatives hide income

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  - info frictions account for  $\frac{1}{4}$  of urban-rural income gap

## EXPERIMENT DESIGN

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## SAMPLING

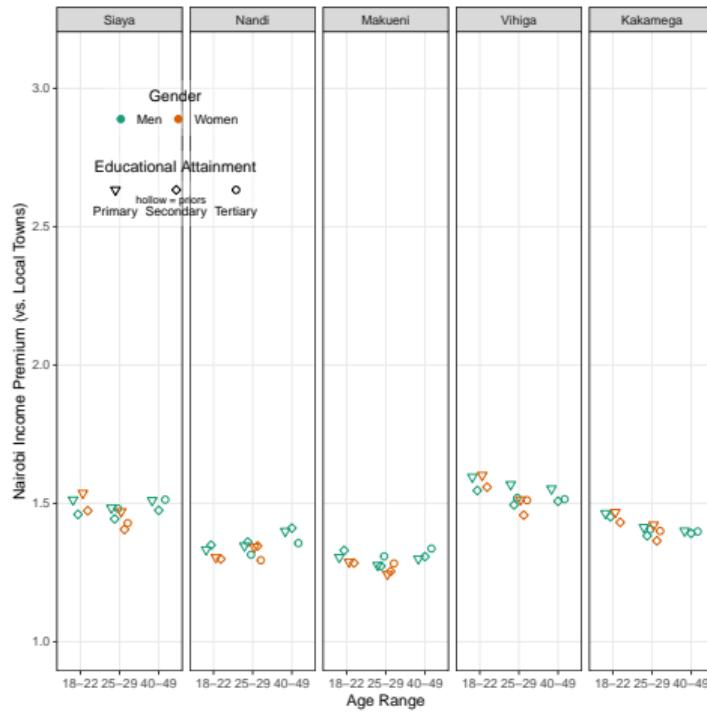
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► *county sampling* ► *village sampling*
- sample 30 households per village for RCT
  - ~30% of avg village size
  - 16,878 households sampled  
► *household sampling*

# RURAL HOUSEHOLDS UNDERESTIMATE NAIROBI INCOME

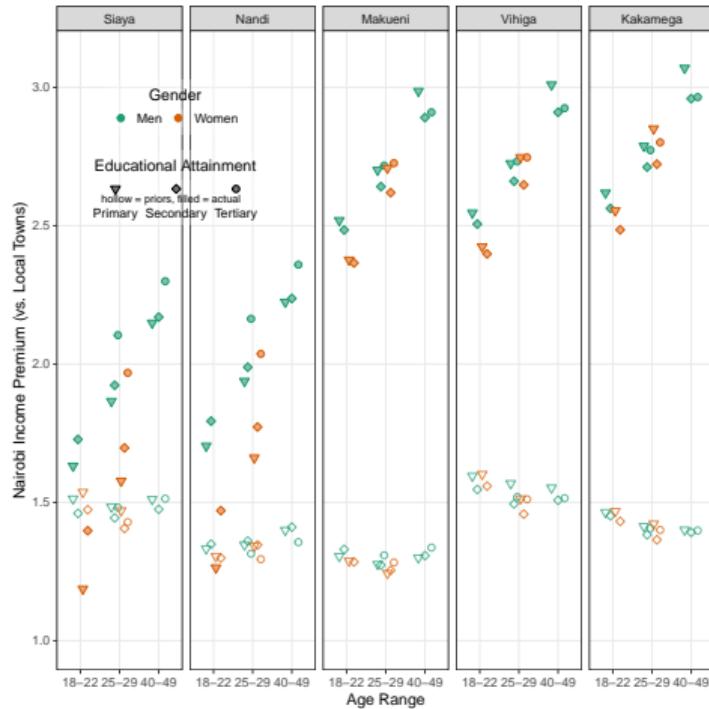
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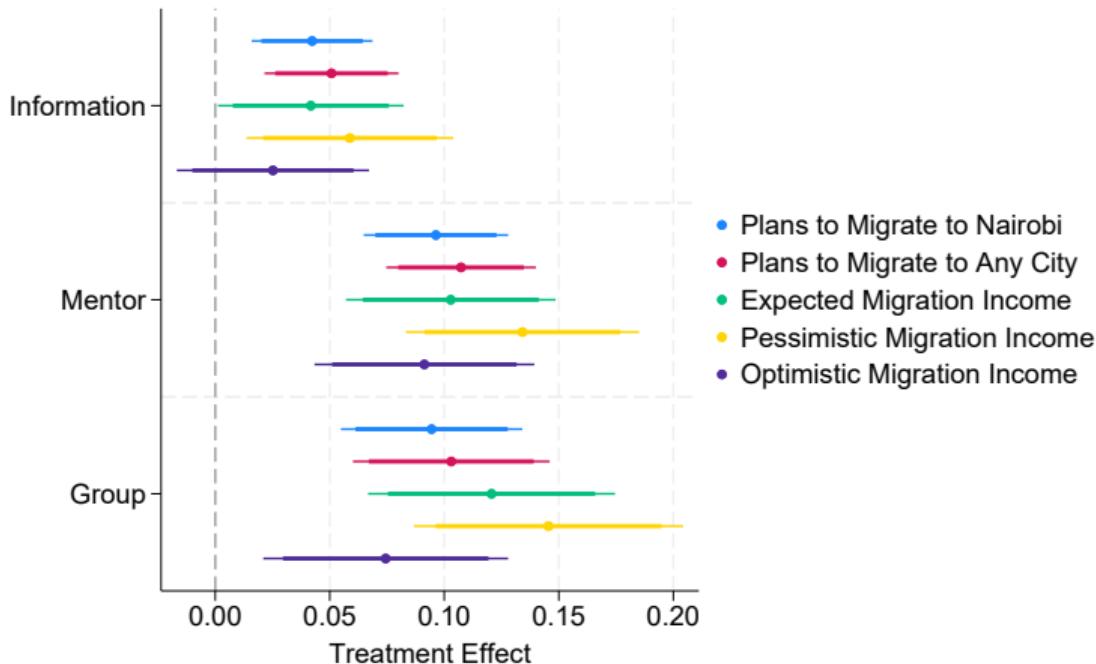
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## EXPERIMENTAL IMPACTS

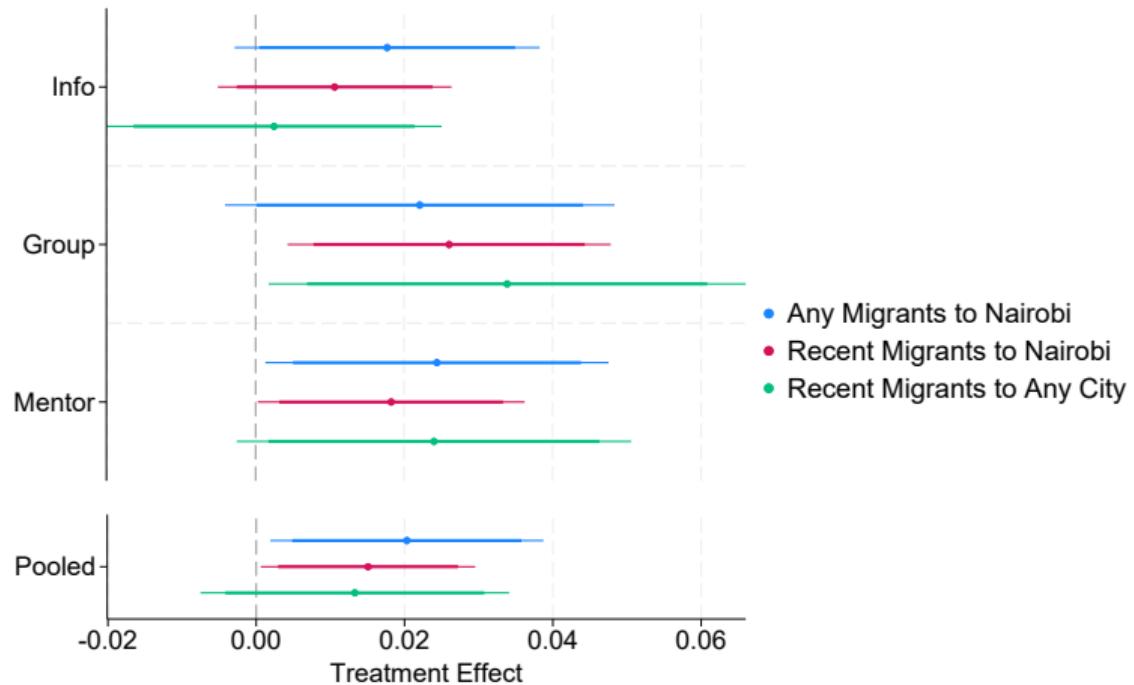
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## BETTER INFO → PERCEIVED URBAN INCOME ↑, MIGRATION PLANS ↑



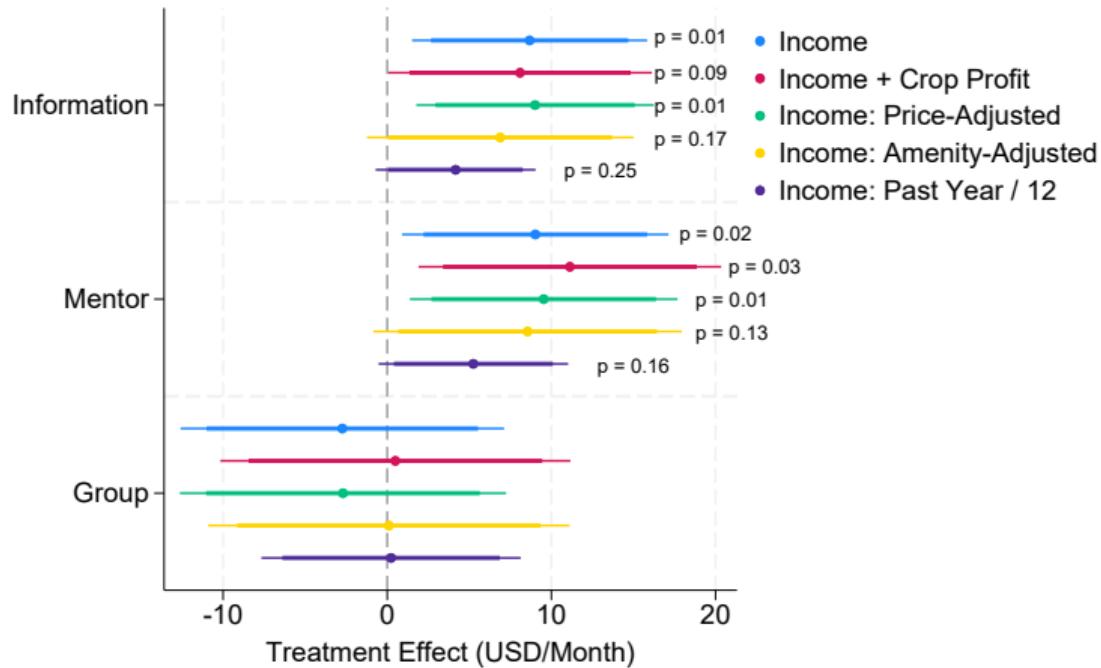
Measured at baseline, after info provision. Units are percentage points (migration plans) or % changes (income beliefs). Bars show 90 and 95% confidence intervals.

## BETTER INFO → MIGRATION ↑



Measured over 16 months after info provision. Units are percentage points.

## BETTER INFO → INCOME ↑, BUT NOT FOR GROUP TREATMENT



p-values on chart test equivalence to Group. ► spillovers

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  - *plot*
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- → economic returns in Group are lower

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  - **positive selection:**
    - villagers with high urban productivity migrate
    - villagers on the migration margin with low migration cost (experienced) have lower urban productivity
- productivities ► consumer problem ► frictions and migration ► estimation ► selection ► positive selection

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- Group: split households into two types at median  $m$ ;
  - low-cost “experienced”:  $\rightarrow$  lower  $\gamma$ 
    - to achieve 12% increase in expected migration income across both types
  - high-cost “inexperienced”:  $\rightarrow$  no change

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- spillovers: small positive income effects on untreated households

## MODEL: IMPORTANCE OF INFO FRICTIONS

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Baseline	0.171	2.639	5.138
Universal Perfect Info	0.219	2.329	4.086

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## CONCLUSION

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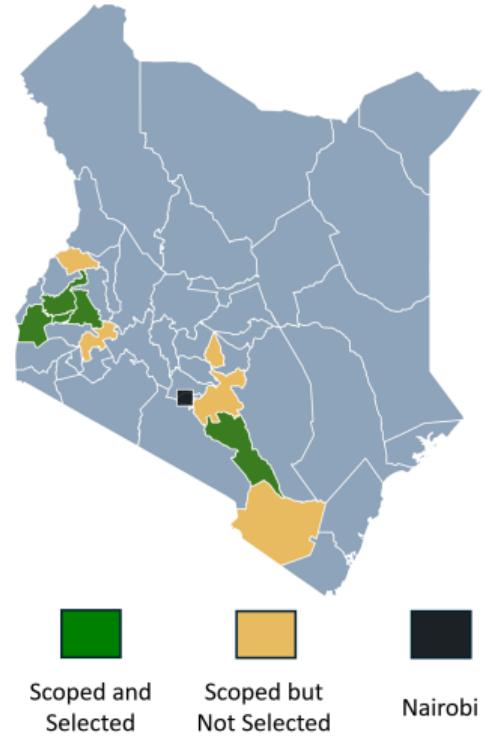
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- inexperienced migrants crowded out from social learning
  - “reaching the novice” is key
- expanding network connections “at destination” appears the best at “reaching the novice”

## STEP 1: COUNTY SELECTION

- Choose 10 counties based on census data, balancing heterogeneity and representativeness
- Short “scoping” surveys in random villages across 10 counties
- Narrow down to five, prioritizing counties with moderate baseline migration



Scoped and  
Selected

Scoped but  
Not Selected

Nairobi

## SAMPLE IS TYPICAL OF RURAL KENYAN POPULATION

	Sample Counties	All Counties	Percentile
% aged 18–50	0.36	0.37	0.41
% with primary degree	0.38	0.38	0.55
% with secondary degree	0.07	0.08	0.39
% with post-secondary degree	0.01	0.02	0.39
% Muslim	0.01	0.00	0.73
Per-capita household income (USD/month)	13.57	23.81	0.26
Density (pop. per sq. km.)	393	288	0.67
Distance to Nairobi (km)	393	306	0.73
% of households migrated out of county	0.23	0.20	0.76
Population	3,972,090	26,384,420	

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## STEP 2: VILLAGE SELECTION AND HOUSEHOLD CENSUS

- Universe of villages from Kenya National Bureau of Statistics
- Randomly select sub-locations (clusters of 10 villages)
  - Exclude bottom 5% and top 10% of county-level population density
- Randomly select one village per sub-location
  - Reduces inter-village spillover risk
  - Exclude villages with < 50 households
- Census entire village  $\implies$  sample of 53,096 households
  - Found 102 households per village (admin data shows 99)
  - Surveyed 90% of all households, sampling weights account for survey probability

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## STEP 3: HOUSEHOLD SELECTION AND RCT

- Randomly select 30 households per village  $\implies$  RCT sample of 16,878 households
  - Stratify on intended migration, oversampling likely migrants (re-weight in estimation)
- Village-level treatment randomization
  - Stratify by county, share intending to migrate to Nairobi, average income
  - Balanced: 3/31 F-tests sig. at 10%,  $\chi^2$ -test with RI (Kerwin, Rostom, Sterck 2024)
- 8-month phone midline: 81% completion, not differential
- 16-month in-person endline: 95% completion, not differential
- Migrant phone surveys: 86% completion, not differential

back

## INTERVENTION DETAILS: INFORMATION

- Total individual income in Nairobi by age, gender, education
  - Wages + (enterprise profit) / # entrepreneurs + (crop profit + other income) / # adults
  - Three quantiles: p25, p50, p75
  - Median incomes relative to a reference point (towns in the home county)
- Employment rates (working 20+ hours in a typical week)
- Rental prices and typical housing amenities
- Source: Kenya Integrated Household Budget Survey 2015–2016
- Treated households get information brochure + script
  - Built-in time for questions, back-and-forth with staff

back

## INTERVENTION DETAILS: GROUP

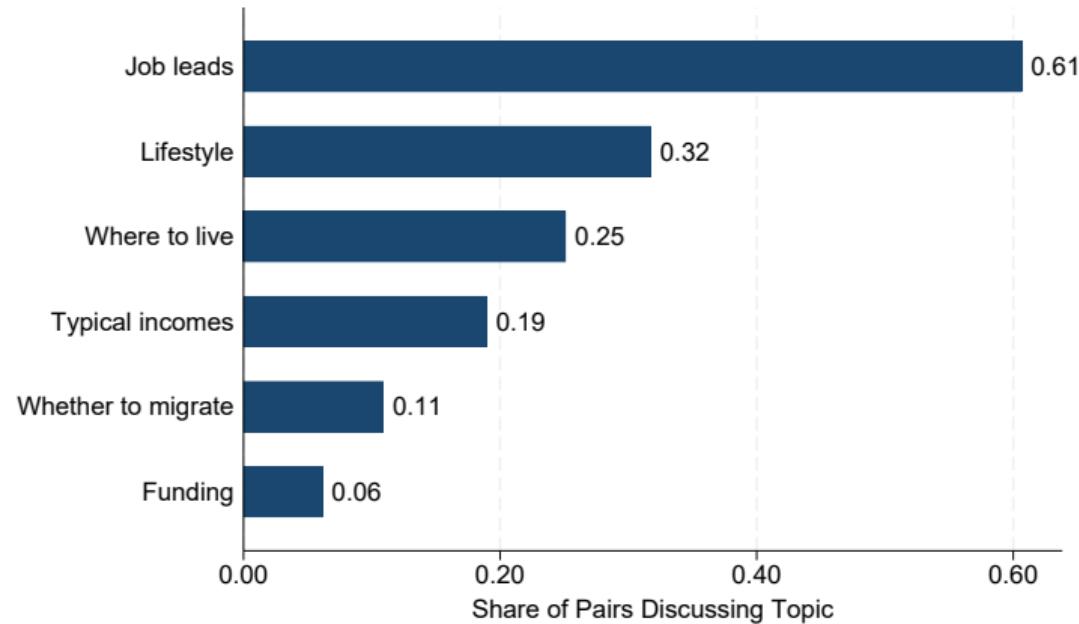
- Each sampled household invited to a group presentation, one or two per village
- Everyone receives the same info sheet, staff reads the same script
- Staff facilitated group discussions about migrating, inviting prior migrants to talk + take questions
- Break into small groups to discuss migrating or coordinating trips
- Attendance was 88% of invited sample
- For those not attending, give individual version during a follow-up visit

back

## INTERVENTION DETAILS: MENTOR

- Basic info sheet and script + offered a 1-on-1 “mentor”
  - We recruited mentors from popular migrant neighborhoods throughout Nairobi
  - Screened on experience (lived in Nairobi for 5+ years)
  - Mentors agreed to speak with them over the phone and/or meet them in Nairobi
  - Mentors received 500 KSh (\$5) per meeting
- Matching was done live as participants enrolled [Matching Details](#)
  - Collected preferences from villagers and characteristics from mentors
  - “Greedy matching”: we gave people the best available match once they enrolled
- Mentors available starting in January 2023 (two months after baseline), program was open for three months.
- 471 households (13% of the sample) participated (staff verified). Of these, 41 physically met in Nairobi.

## WHAT DID MENTORS TALK ABOUT?



Data from midline surveys of household heads.

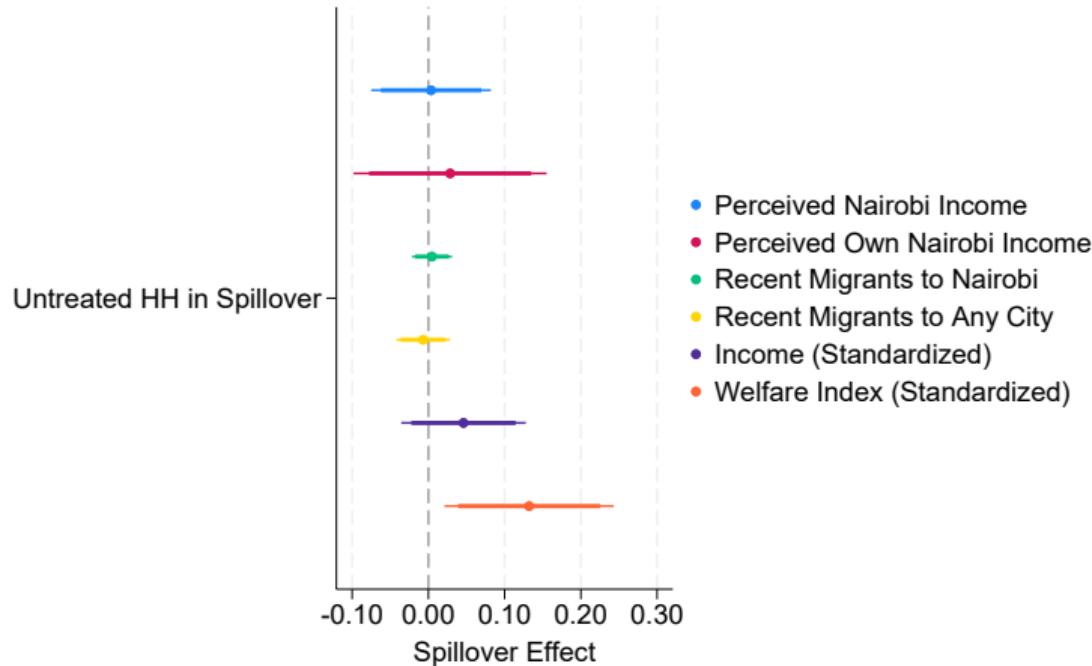
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## ASSESSING BASELINE INFORMATION GAPS

- Elicit income beliefs about Nairobi and reference towns (towns in home county) during census surveys ( $N = 53,096$ )
- Compare to estimates from representative surveys
- Ask belief about specific age-by-gender cells, randomized across households
- Each household was asked the same question for primary school, secondary school, and college graduation
- Compute “Nairobi premium” for group  $g$  as the mean belief about Nairobi over the mean belief about the reference town

back

## ECONOMIC SPILLOVERS WITHOUT INFO SPILLOVERS



Sample includes untreated households in Pure Control and Spillover villages. Measured 16 months after info provision. Units are % changes (perceived income), percentage points (migration), or standard deviations (income, welfare).

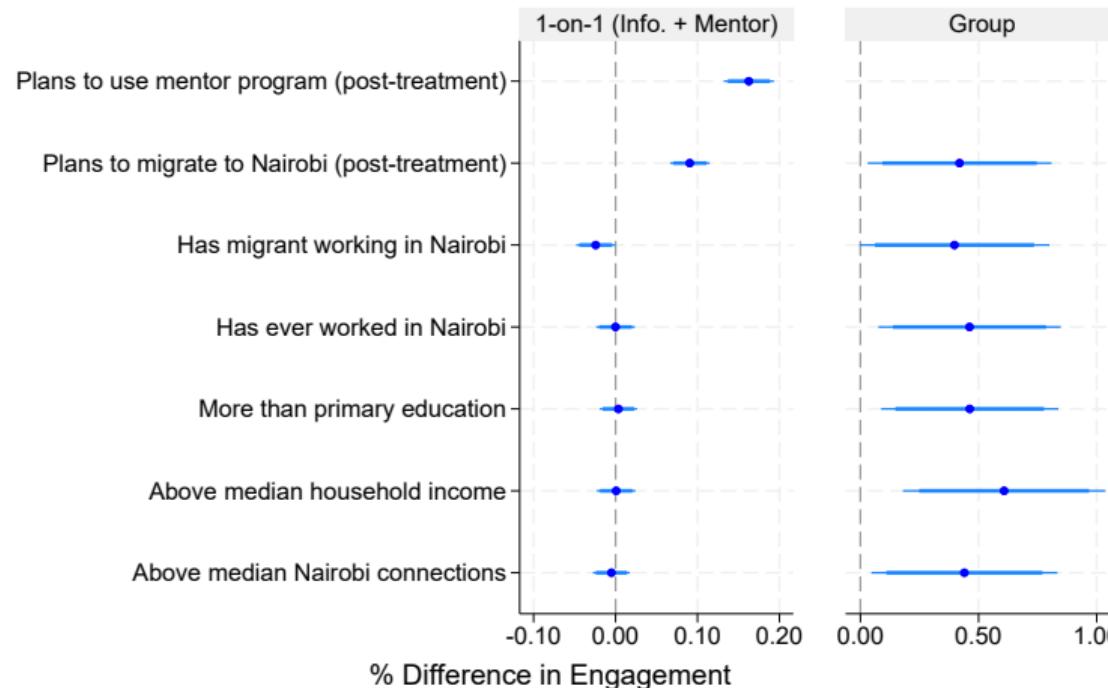
► why didn't info diffuse?

## WHY DIDN'T INFORMATION DIFFUSE?

- Recall that the average household underestimates the share of its village with a migrant by almost half
- Are there strategic incentives to conceal the information given during treatment?
  - Informing others may make them more likely to co-migrate...
  - But it may become harder to hide migration status or income
- We find that households with more potential creditors in the village update less in Spillover (vs. Pure Control) villages [Table](#)
  - No differences for non-financial relationships
  - Helps explain the success of mentors: they are outside rural households' risk-sharing networks

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## CHANNEL 1: INEXPERIENCED MIGRANTS ARE LESS ENGAGED IN GROUP TREATMENTS, BUT NOT 1-ON-1 TREATMENTS\*



## WHEN EXPERIENCED MIGRANTS LEAD GROUP DISCUSSIONS, THEY PRIMARILY INFLUENCE OTHER EXPERIENCED MIGRANTS\*

Outcome: Recent Migrants to Nairobi	Measure of Experience, X		
	Has Migrant in Nairobi	Has Worker in Nairobi	Ever Worked in Nairobi
Leader of Type X × X × Group	0.13*** (0.03)	0.05* (0.03)	0.06* (0.03)
Leader of Type X × Group	-0.02 (0.02)	0.01 (0.02)	-0.00 (0.02)
X × Group	0.07*** (0.01)	0.06*** (0.01)	0.03*** (0.01)
Group	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
Group Mean (X)	0.36	0.29	0.43
Group Mean (Leader of Type X)	0.71	0.62	0.72
Observations	15,468	15,468	15,468

back

## WHEN EXPERIENCED MIGRANTS LEAD GROUP DISCUSSIONS, THEY PRIMARILY INFLUENCE OTHER EXPERIENCED MIGRANTS\*

Outcome: Recent Migrants to Nairobi	Measure of Experience, X		
	Has Migrant in Nairobi	Has Worker in Nairobi	Ever Worked in Nairobi
Leader of Type $X \times X \times$ Group	0.13*** (0.03)	0.05* (0.03)	0.06* (0.03)
Leader of Type $X \times$ Group	-0.02 (0.02)	0.01 (0.02)	-0.00 (0.02)
$X \times$ Group	0.07*** (0.01)	0.06*** (0.01)	0.03*** (0.01)
Group	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
Group Mean ( $X$ )	0.36	0.29	0.43
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## CHANNEL 2: INFO. TREATMENT FACILITATES DIS-ASSORTATIVE CO-MIGRATION\*

	Co-Migrated to Nairobi		Co-Migrated to Nairobi With More Experienced Migrant	
Info	0.006*** (0.002)	0.007*** (0.002)	0.006*** (0.002)	0.007*** (0.002)
Group	0.004 (0.003)	0.002 (0.002)	0.002 (0.002)	0.002 (0.001)
Mentor	0.001 (0.002)	0.003 (0.002)	0.001 (0.002)	0.002 (0.001)
Info × Mig. In Nairobi		-0.005 (0.005)		-0.004 (0.004)
Group × Mig. In Nairobi		0.008 (0.009)		0.003 (0.008)
Mentor × Mig. In Nairobi		-0.006 (0.004)		-0.003 (0.003)
Control Mean	0.008	0.008	0.006	0.006
Observations	15,468	15,468	15,468	15,468

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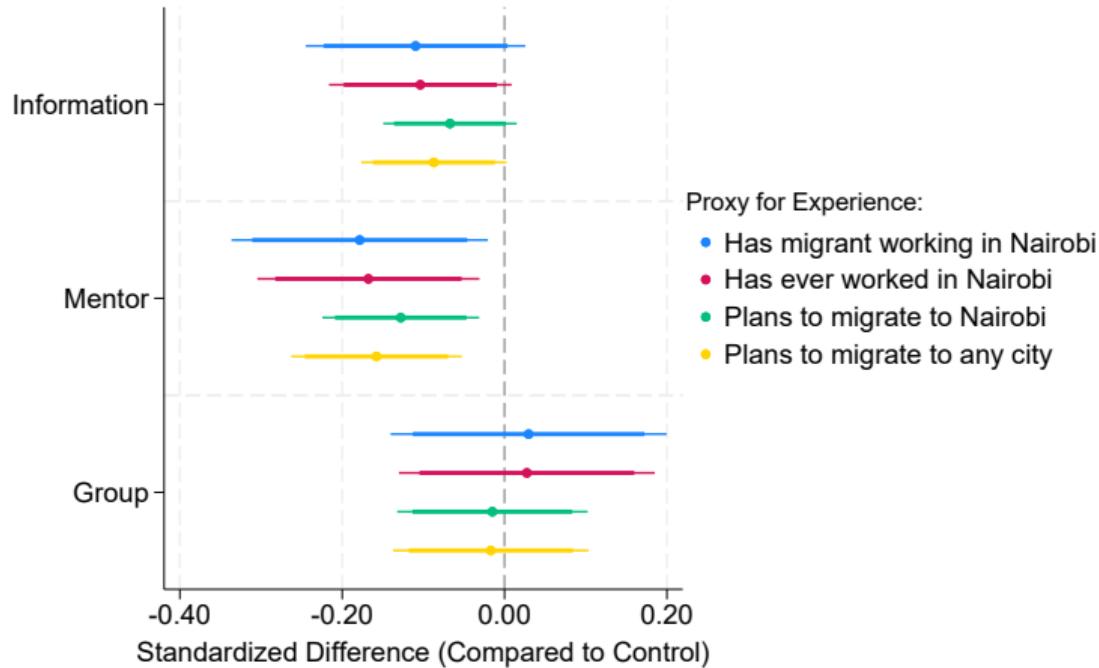
back

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Info	0.006*** (0.002)	0.007*** (0.002)	0.006*** (0.002)	0.007*** (0.002)
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back

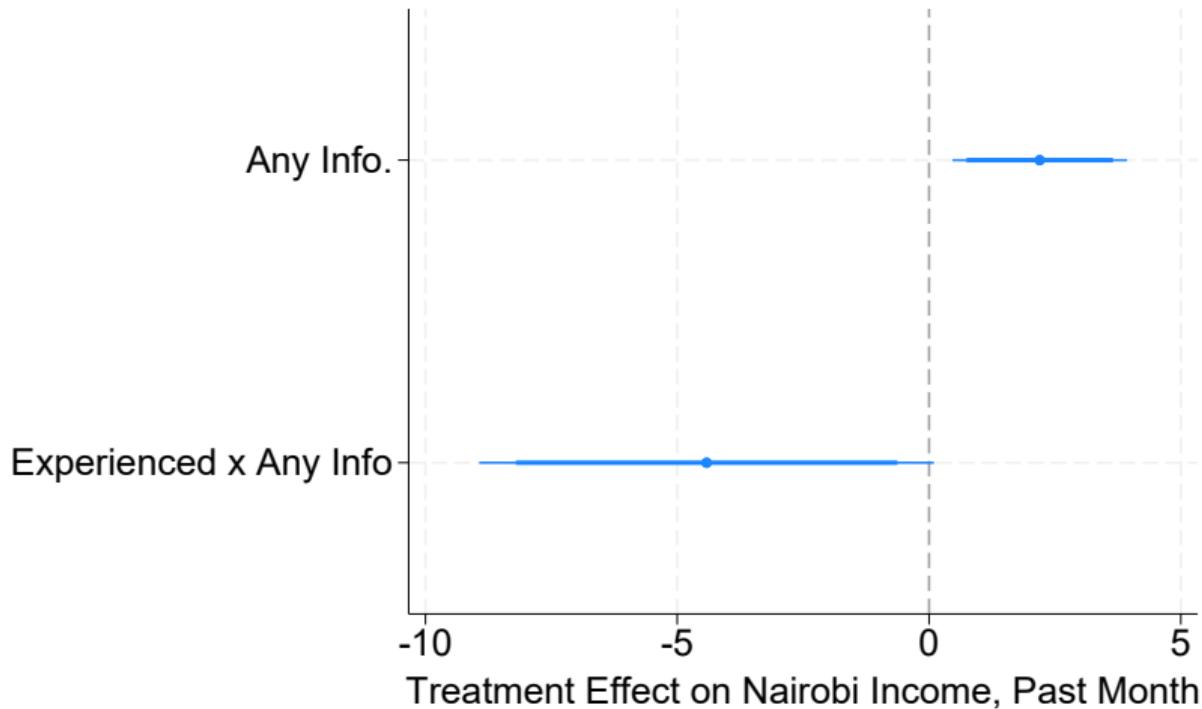
## INFO. AND MENTOR INDUCE LOW-EXPERIENCE MIGRATION COMPARED TO GROUP\*



Each outcome is a baseline variable. Sample includes households with migrants at endline.

[back](#)

## INEXPERIENCED MIGRANTS HAVE HIGHER RETURNS AT THE MARGIN



*Any Info* is a pooled treatment variable. *Experienced* = 1 if the hh had a migrant working in Nairobi before treatment.

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## HOUSEHOLD ENDOWMENTS

- each HH  $i$  draws urban, rural non-agricultural, rural agricultural productivities
  - lognormal, possibly correlated ( $d$ )

$$z_{u,i}^n = \exp \varepsilon_{u,i}^n,$$

$$\varepsilon_{u,i}^n \sim \mathcal{N}(0, \sigma_u^2)$$

$$z_{r,i}^n = \exp (d \log z_{u,i}^n + \varepsilon_{r,i}^n)$$

$$\varepsilon_{r,i}^n \sim \mathcal{N}(0, \sigma_r^2)$$

$$z_{r,i}^a = \exp (d \log z_{u,i}^n + \varepsilon_{r,i}^a)$$

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back

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$$\varepsilon_{r,i}^a \sim \mathcal{N}(0, \sigma_r^2)$$

- households draw a log-normal migration cost  $m_i$

back

## CONSUMER PROBLEM

$$\max_{c_i^a, c_i^n} \log(c_i^a - \bar{a}) + \nu \log(c_i^n)$$

such that

$$p^a c_i^a + p^n c_i^n \leq y_i + \pi + \tilde{m}$$

back

## FRICtIONS AND MIGRATION

- rural household's options:
  - stay in  $r$ , work in  $n$ , earn  $y_{r,i}^n = z_{r,i}^n w_r^n$
  - stay in  $r$ , work in  $a$ , earn  $y_{r,i}^a = z_{r,i}^a w_r^a$
  - migrate to  $u$ , work in  $n$ , earn  $y_{r,i}^{nm} = \frac{1}{1+m_i} z_{r,i}^n w_u^n$ 
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- information friction  $\gamma_i \rightarrow$  underestimation of urban income
  - $y_{r,i}^n$  and  $y_{r,i}^a$  perceived accurately
  - $y_{r,i}^{nm}$  underestimated as  $\frac{1}{1+\gamma_i} y_{r,i}^{nm}$

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  - $y_{r,i}^{nm}$  underestimated as  $\frac{1}{1+\gamma_i} y_{r,i}^{nm}$
- migrate iff

$$\frac{1}{1+\gamma_i} y_{r,i}^{nm} \geq \max \left\{ y_{r,i}^n, y_{r,i}^a \right\}$$

back

## ESTIMATION

- assigned parameters: labor share  $\theta$ , non-ag cons. weight  $\nu$ , migration cost disp.  $\sigma_m$ , productivities  $A_u^n, A_r^a$

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- estimated parameters:

Parameter	Value	Moment	Data	Model
$\bar{a}$	5.569	food cons. share	0.345	0.345
$A_r^n$	0.113	median urban-rural inc. gap	5.147	5.138
$\sigma_u$	1.547	SD of log urban inc.	1.491	1.492
$\sigma_r$	1.982	SD of log rural inc.	1.569	1.569
$d$	0.075	log urban-rural inc. slope	0.065	0.065
$\mu_m$	2.869	migration rate	0.171	0.171

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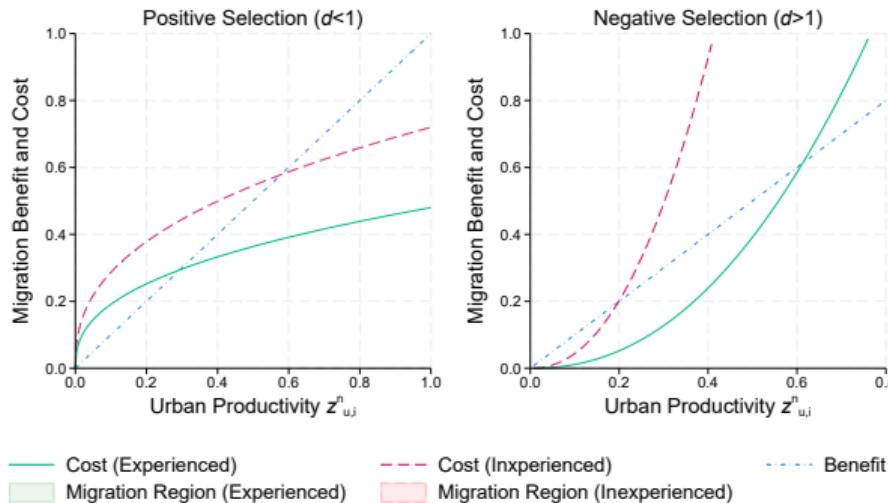
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- info friction  $\gamma_i$ :
    - assume common friction:  $\gamma_i = \gamma$
    - avg  $\frac{\text{true urban income}}{\text{perceived urban income}} = 0.559$
- $$\rightarrow \gamma = \frac{1}{0.559} - 1 = 0.789$$

back

## SELECTION AND RETURNS IN DIFFERENT ENVIRONMENTS

- consider a HH “type” with common  $(m_i, \varepsilon_{r,i}^n, \varepsilon_{r,i}^a)$  but varying  $\varepsilon_{u,i}^n$  (and thus  $z_{u,i}^n$ )

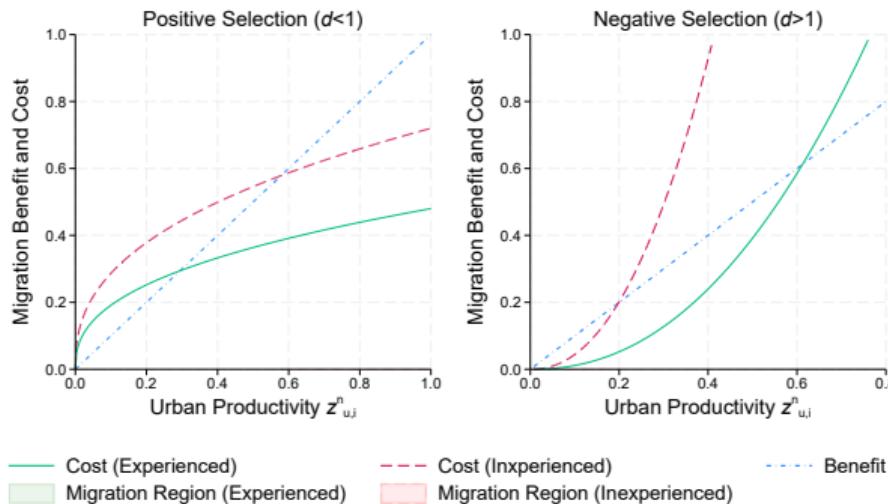


Benefit =  $z_{n,i}$ . Cost =  $z_{a,i} w_a (1 + m_i)(1 + \gamma_i)$ . Inexperience is modeled as a high  $m_i$ .

back

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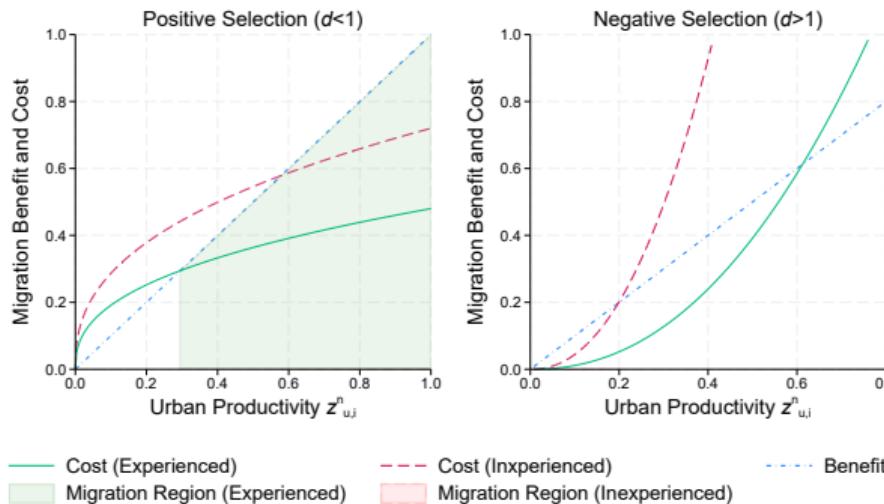


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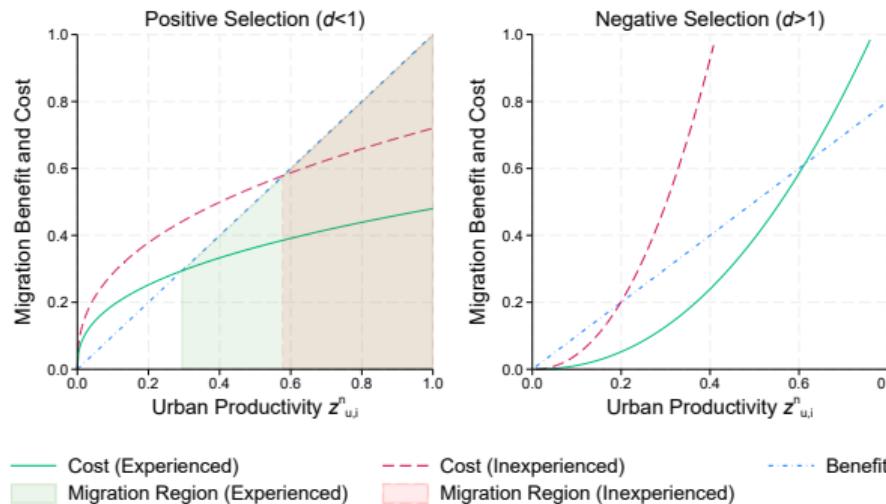


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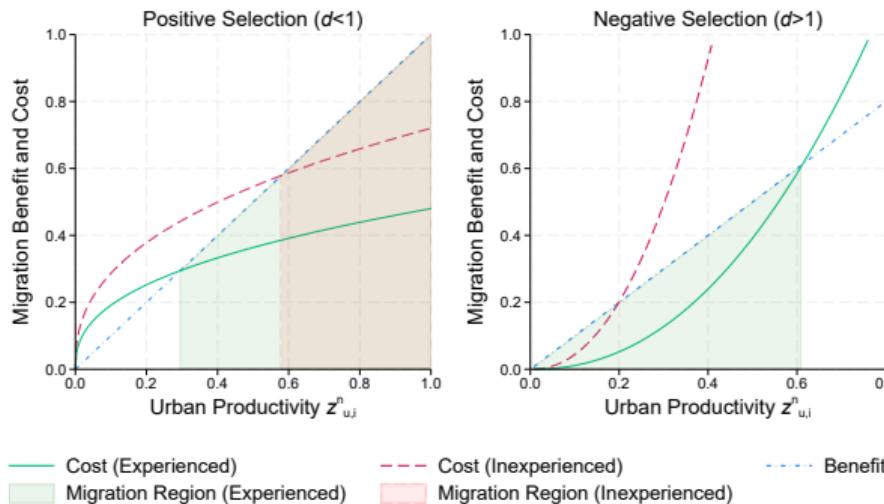


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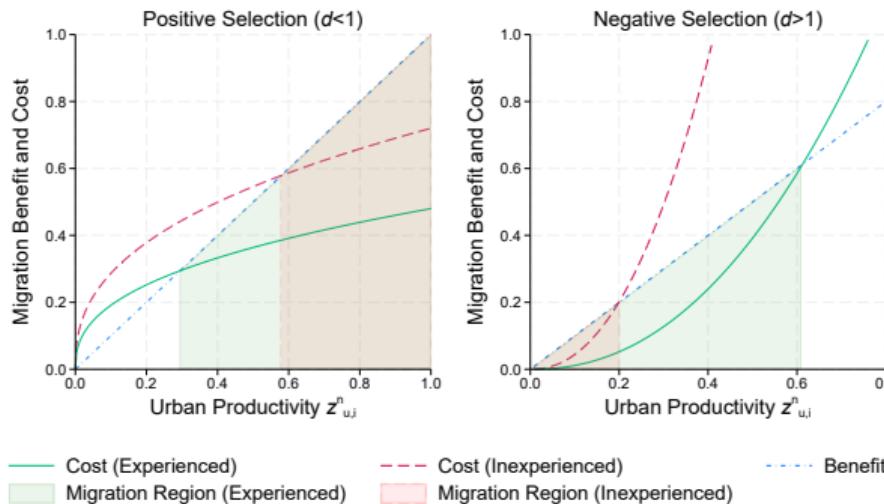


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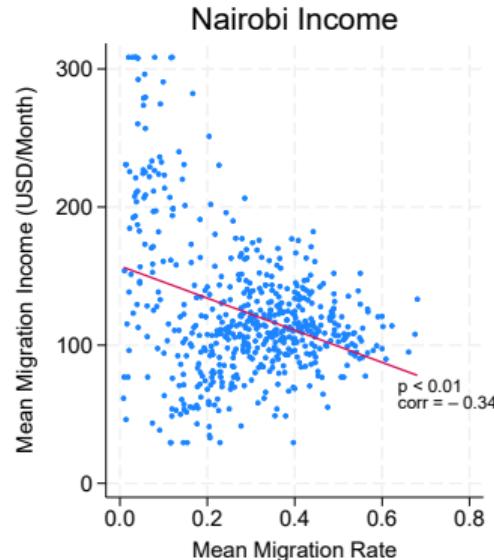
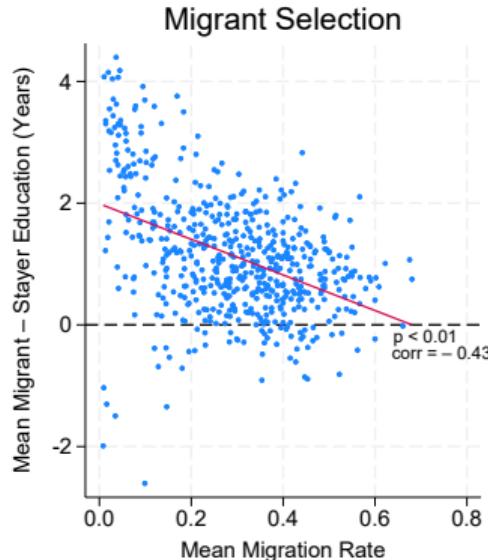
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## POSITIVE SELECTION

- model: estimated  $d = 0.075 \rightarrow$  positive selection

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- model: estimated  $d = 0.075 \rightarrow$  positive selection
- data: positive selection in most villages especially in high-cost villages



## SELECTION

- consider a HH “type” with common  $(\gamma_i, m_i, \varepsilon_{r,i}^n, \varepsilon_{r,i}^a)$  but varying  $\varepsilon_{u,i}^n$  (and thus  $z_{u,i}^n$ )

back

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- threshold urban productivity  $\hat{z}_{n,i}$  (worker indifferent between migrating/staying):

$$\underbrace{\frac{1}{1+\gamma_i} \frac{1}{1+m_i} \hat{z}_{u,i}^n w_u^n}_{\text{perceived urban inc.}} = \max \left\{ \underbrace{(\hat{z}_{u,i}^n)^d \exp \varepsilon_{r,i}^n w_r^n}_{\text{rural non-ag inc.}}, \underbrace{(\hat{z}_{u,i}^n)^d \exp \varepsilon_{r,i}^a w_r^a}_{\text{rural ag inc.}} \right\}$$

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- if  $d < 1$  (rural productivity rises **less** than 1-to-1 with urban productivity):
  - **positive** selection: everyone with  $z_{u,i}^n > \hat{z}_{u,i}^n$  migrates
  - $\frac{\partial \hat{z}_{u,i}^n}{\partial \gamma_i} > 0$ ,  $\frac{\partial \hat{z}_{u,i}^n}{\partial m_i} > 0$  (frictions  $\uparrow \rightarrow$  threshold  $\uparrow$ )

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  - $\frac{\partial \hat{z}_{u,i}^n}{\partial \gamma_i} > 0, \frac{\partial \hat{z}_{u,i}^n}{\partial m_i} > 0$  (frictions  $\uparrow \rightarrow$  threshold  $\uparrow$ )
- If  $d > 1$  (rural productivity rises **more** than 1-to-1 with urban productivity):
  - **negative** selection: everyone with  $z_{u,i}^n < \hat{z}_{u,i}^n$  migrates
  - $\frac{\partial \hat{z}_{u,i}^n}{\partial \gamma_i} < 0, \frac{\partial \hat{z}_{u,i}^n}{\partial m_i} < 0$  (frictions  $\uparrow \rightarrow$  threshold  $\downarrow$ )

## EXPERIMENTAL IMPACTS

### Model: Experimental Impacts

	Partial Equilibrium		General Equilibrium		
	Migration rate change	Avg income change	Migration rate change	Avg income change	Avg income change, spillover
Info	0.004	0.113	0.004	0.103	0.001
Mentor	0.010	0.287	0.009	0.272	0.003
Group	0.016	0.155	0.015	0.154	0.006

“Migration rate change” is the difference in migration rate among treated households. “Avg income change” is the average relative change in observed income (gross of migration cost) for the treated households. “Avg income change, spillover” is the average relative change in observed income for the untreated rural households.

## SCALING THE INTERVENTIONS

### Model: Aggregate Impacts of Universal Treatments

	Migration Rate	Real Non-Agric. GDP	Real Agric. GDP	Agricultural Productivity Gap	Urban-Rural Income Gap
Baseline	0.171	1.000	1.000	2.639	5.138
Info	0.173	1.004	1.000	2.620	5.064
Mentor	0.178	1.013	0.999	2.593	4.962
Perfect Info	0.219	1.060	0.995	2.329	4.086

Universal treatments are applied to all rural households. All economies are solved in general equilibrium. Real non-agricultural and agricultural GDPs are expressed relative to the baseline.

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