Reaching the Novice or Nudging the Expert? Networks, Information, and Experimental Returns to Migration

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Stockman

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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  - pervasive under-estimation of urban income premium (avg: 45%)
  - because: experimenting is costly, migrant relatives hide income

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- **RCT** in Kenya: provide **better info** about urban labor markets to rural households

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

Contributions

1. causes of rural-urban income gaps (Bryan, Chowdhury, Mobarak, 2014; Imbert and Papp, 2019, 2020; Cai, 2020; Baseler et al., 2025; Lagakos et al., 2023; Morten and Oliveira, 2024)

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2. social networks and migration outcomes (Munshi 2003, 2020; Baseler, 2023; Blumenstock, Chi, and Tan, 2025)
   - experienced low-return migrants crowd-out inexperienced high-return migrants from group discussion
   - destination (not origin) links improve selection into migrating

Experiment Design

Sampling

- sample 560 villages from 5 counties, census all 53,096 households
  - sample is typical of rural Kenyan population ▶ *comparison*

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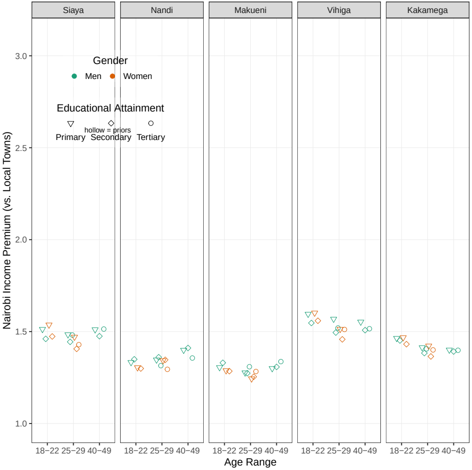
- sample 30 households per village for RCT
  - $\sim$30% of avg village size
  - 16,878 households sampled

  ▶ *household sampling*

Rural Households Underestimate Nairobi Income

elicit beliefs about Nairobi income for different demographic groups...



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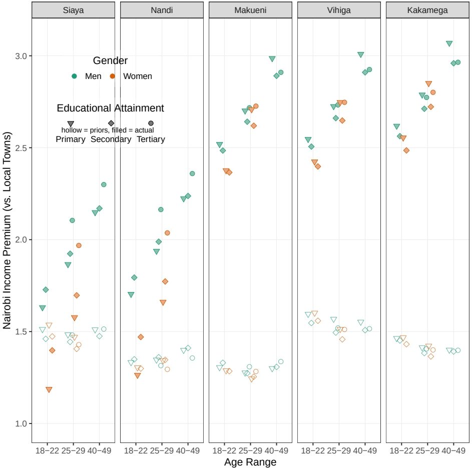

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Intervention: Villages Randomly Assigned to Treatments

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  - avg income, income distribution in Nairobi by demographic group
  - employment rates
  - rental prices and amenities
  - time for Q&A with staff

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  - spoke over the phone, some met in person in Nairobi ▶ *about what?*

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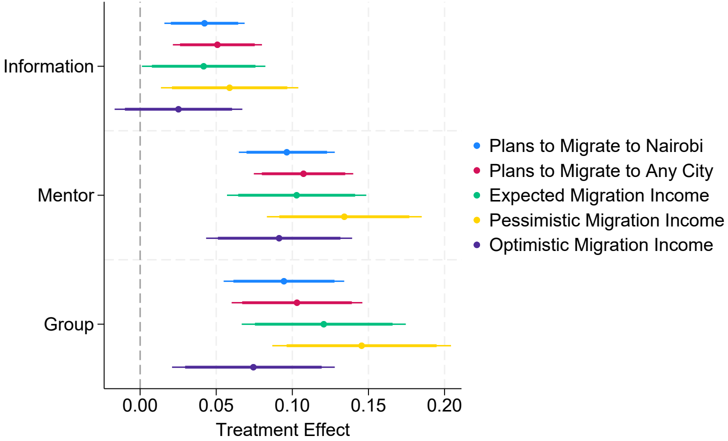
- **control**: no intervention

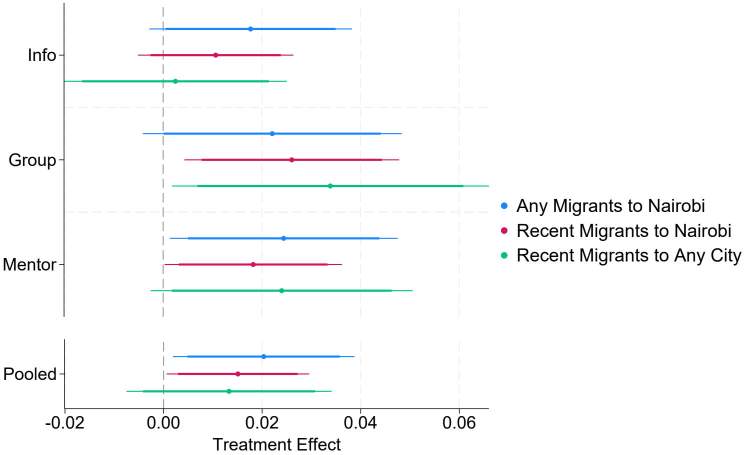
Experimental Impacts

Better Info → Perceived Urban Income ↑, Migration Plans ↑



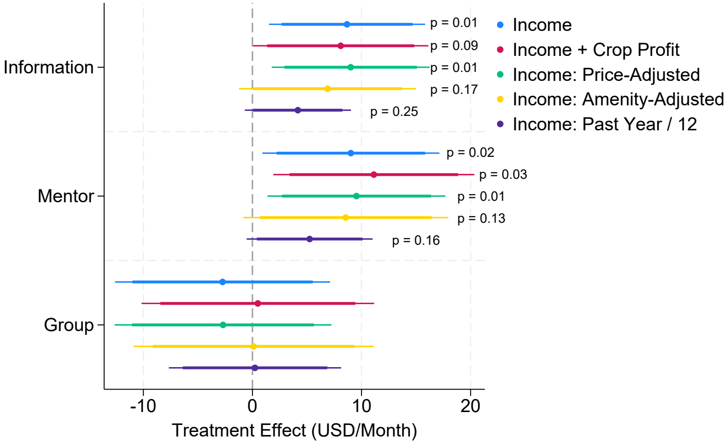
Measured at baseline, after info provision. Units are percentage points (migration plans) or % changes (income beliefs). Bars show 90 and 95% confidence intervals.

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*

Why is Group Worse Economically? Adverse Selection

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  - *plot*
    - whereas experienced and inexperienced engage equally in 1-on-1s

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- $\rightarrow$ economic returns in Group are lower

Model

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- sectors: rural agriculture, rural non-agriculture, urban non-agriculture

▶ *consumer problem*

Household Endowments

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

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z^n_{u,i} &= \exp \varepsilon^n_{u,i}, & \varepsilon^n_{u,i} &\sim \mathcal{N}(0, \sigma^2_u) \\
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- households draw a log-normal migration cost m_i

- rural household's options:
  - stay in r, work in n, earn $y^{n}_{r,i} = z^{n}_{r,i} w^{n}_{r}$
  - stay in r, work in a, earn $y^{a}_{r,i} = z^{a}_{r,i} w^{a}_{r}$
  - migrate to u, work in n, earn $y^{nm}_{r,i} = \frac{1}{1+m_i} z^{n}_{r,i} w^{n}_{u}$
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- information friction $\gamma_i \rightarrow$ underestimation of urban income
  - $y^n_{r,i}$ and $y^a_{r,i}$ perceived accurately
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- migrate iff

$$\frac{1}{1+\gamma_i} y^{nm}_{r,i} \geq \max \left\{ y^n_{r,i},\ y^a_{r,i} \right\}$$

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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
σ_u	1.547	SD of log urban inc.	1.491	1.492
σ_r	1.982	SD of log rural inc.	1.569	1.569
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- info friction γ_i:
  - assume common friction: $\gamma_i = \gamma$
  - avg $\frac{\text{true urban income}}{\text{perceived urban income}} = 0.559$

  $\rightarrow \gamma = \frac{1}{0.559} - 1 = 0.789$

Selection and Returns in Different Environments

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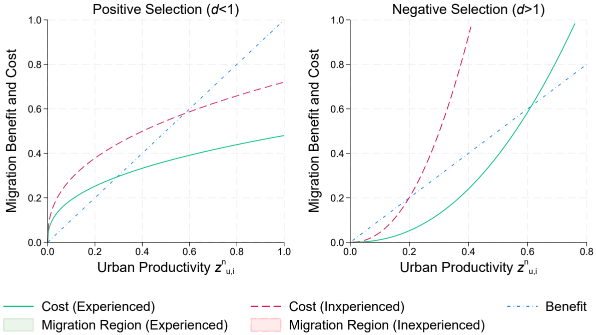

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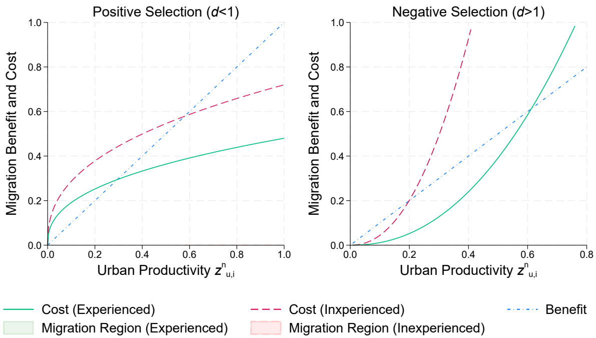

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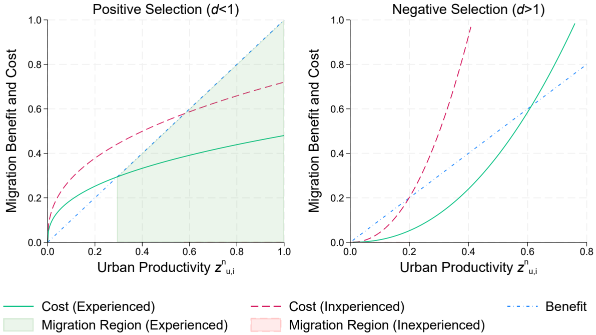

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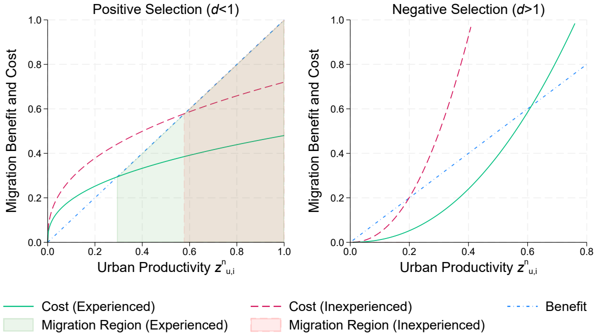

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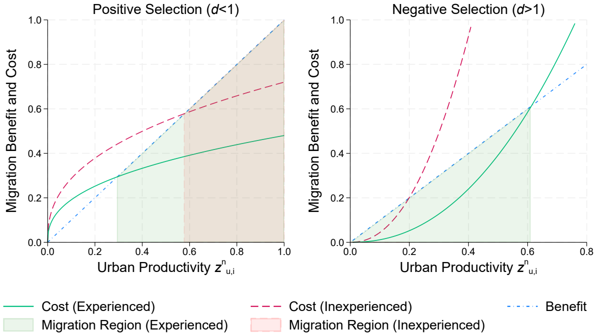

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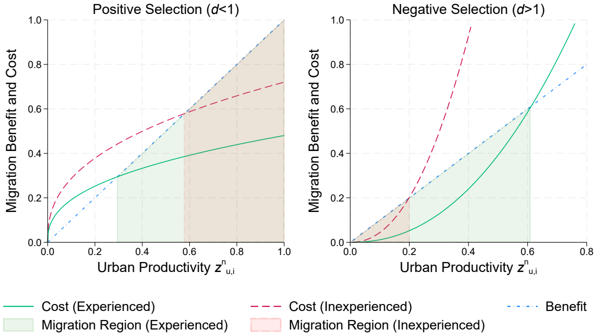

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Positive Selection

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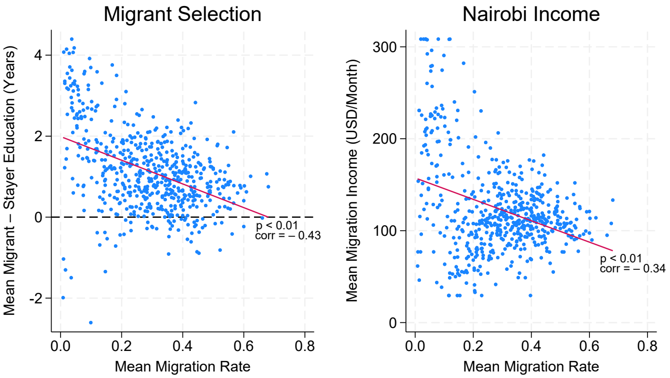
- data: positive selection in most villages, especially in high-cost villages



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

Model: Experimental Impacts

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	migration rate change		avg income change	
	model	data	model	data

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Mentor	0.010	0.018-0.024	0.287	0.093

Model: Experimental Impacts

- Partial Equilibrium effects compared to data:

	migration rate change		avg income change	
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Model: Importance of Info Frictions

- fix the understatement of urban income ($\gamma_i = 0$ for all households):

	migration rate	agricultural productivity gap	urban-rural income gap

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Baseline	0.171	2.639	5.138
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Conclusion

Information Gaps are Large and Suppress Migration

- offering better info is a cost-effective way to boost migration and income
  - costs $\approx$ \$10 one-time visit for \$9 monthly gains

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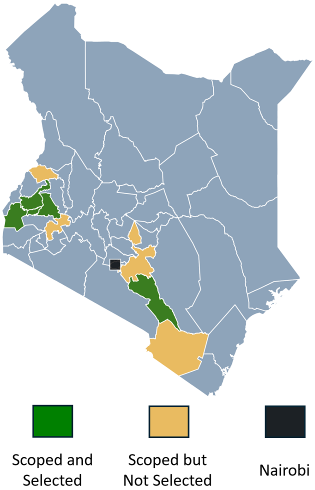
- inexperienced migrants crowded out from social learning
  - "reaching the novice" is key
- expanding network connections "at destination" appears the best at "reaching the novice"

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



back

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	

back

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

back

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%, χ^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

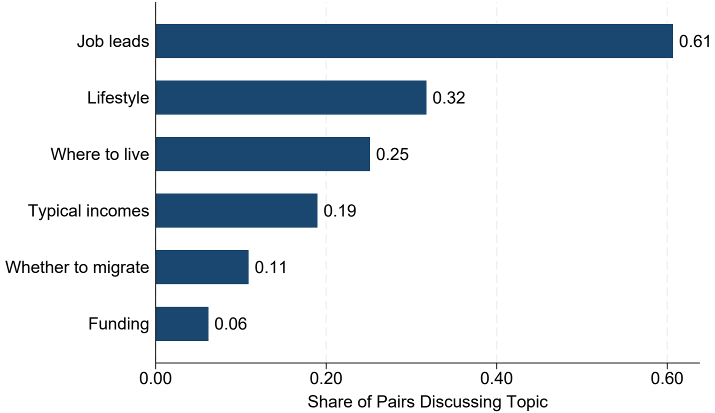
back

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.

back

What did mentors talk about?



Data from midline surveys of household heads.

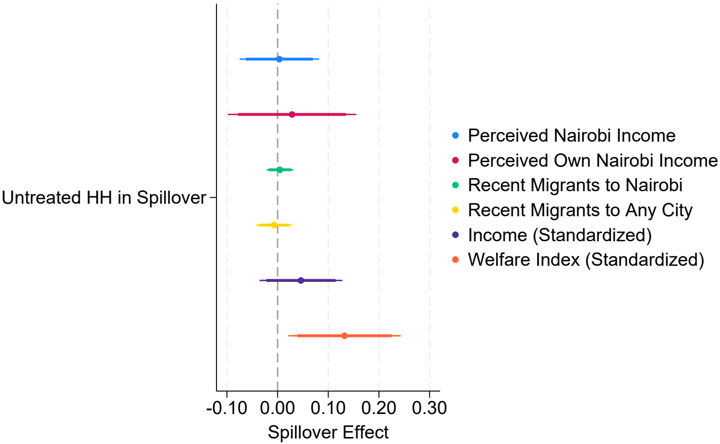
back

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?*

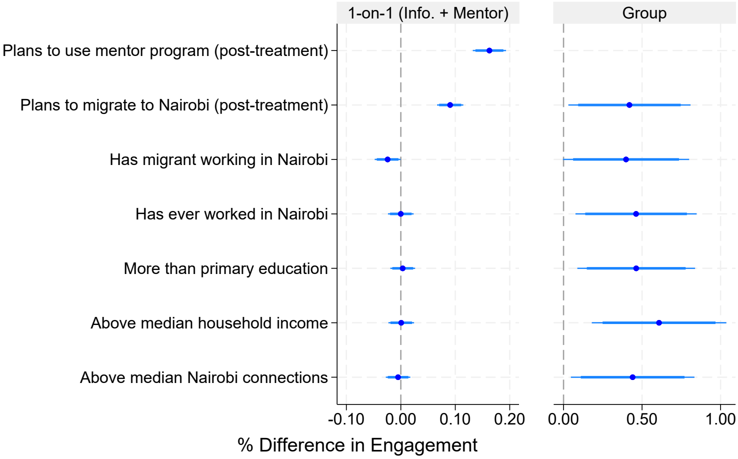
back

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

back

Channel 1: Inexperienced migrants are less engaged in group treatments, but not 1-on-1 treatments*



back

When experienced migrants lead group discussions, they primarily influence other experienced migrants*

	Measure of Experience, X		
Outcome: Recent Migrants to Nairobi	Has Migrant in Nairobi	Has Worker in Nairobi	Ever Worked in Nairobi
Leader of Type $X \times X \times$ Group	0.13^{***}	0.05^{*}	0.06^{*}
	(0.03)	(0.03)	(0.03)
Leader of Type $X \times$ Group	-0.02	0.01	-0.00
	(0.02)	(0.02)	(0.02)
$X \times$ Group	0.07^{***}	0.06^{***}	0.03^{***}
	(0.01)	(0.01)	(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

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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***	0.007***	0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Group	0.004	0.002	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.001)
Mentor	0.001	0.003	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.001)
Info $\times$ Mig. In Nairobi		-0.005		-0.004
		(0.005)		(0.004)
Group $\times$ Mig. In Nairobi		0.008		0.003
		(0.009)		(0.008)
Mentor $\times$ Mig. In Nairobi		-0.006		-0.003
		(0.004)		(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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Group	0.004	0.002	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.001)
Mentor	0.001	0.003	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.001)
Info × Mig. In Nairobi		-0.005		-0.004
		(0.005)		(0.004)
Group × Mig. In Nairobi		0.008		0.003
		(0.009)		(0.008)
Mentor × Mig. In Nairobi		-0.006		-0.003
		(0.004)		(0.003)
Control Mean	0.008	0.008	0.006	0.006
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	(0.002)	(0.002)	(0.002)	(0.001)
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		(0.009)		(0.008)
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		(0.004)		(0.003)
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Group	0.004	0.002	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.001)
Mentor	0.001	0.003	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.001)
Info × Mig. In Nairobi		-0.005		-0.004
		(0.005)		(0.004)
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		(0.009)		(0.008)
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Group	0.004	0.002	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.001)
Mentor	0.001	0.003	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.001)
Info × Mig. In Nairobi		-0.005		-0.004
		(0.005)		(0.004)
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		(0.009)		(0.008)
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		(0.004)		(0.003)
Control Mean	0.008	0.008	0.006	0.006
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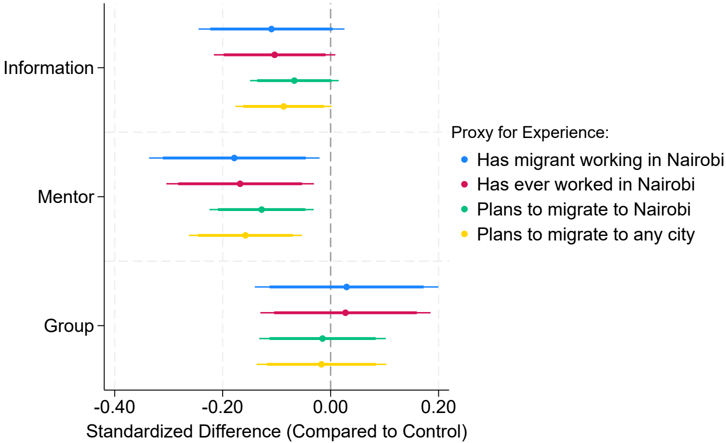
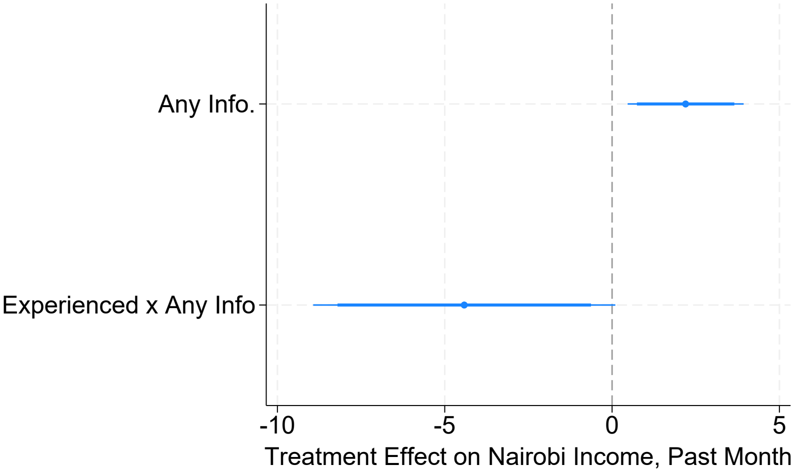
back

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. back

Consumer Problem

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

such that

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

back

Selection

- consider a HH "type" with common $(\gamma_i, m_i, \varepsilon^n_{r,i}, \varepsilon^a_{r,i})$ but varying $\varepsilon^n_{u,i}$ (and thus $z^n_{u,i}$)

back

Selection

- consider a HH "type" with common $(\gamma_i, m_i, \varepsilon^n_{r,i}, \varepsilon^a_{r,i})$ but varying $\varepsilon^n_{u,i}$ (and thus $z^n_{u,i}$)
- threshold urban productivity $\widehat{z}_{n,i}$ (worker indifferent between migrating/staying):

$$\underbrace{\frac{1}{1+\gamma_i}\frac{1}{1+m_i}\widehat{z}^n_{u,i}w^n_u}_{\text{perceived urban inc.}} = \max\left\{\underbrace{(\widehat{z}^n_{u,i})^d \exp \varepsilon^n_{r,i} w^n_r}_{\text{rural non-ag inc.}}, \underbrace{(\widehat{z}^n_{u,i})^d \exp \varepsilon^a_{r,i} w^a_r}_{\text{rural ag inc.}}\right\}$$

back

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

back

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

back

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.

back

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.

back