Reevaluating Agricultural Productivity Gaps with Longitudinal Microdata

Presentation Slides

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Agriculture in Economic Development

- The shift "out of agriculture" has long been seen as a central component of economic development:
- This **"structural transformation"** was a focus of early development thinkers (Rosenstein-Rodan, Lewis, Rostow, Harris & Todaro, Kuznets, etc.).

- Long-standing debate among scholars and policymakers about whether to nurture **agricultural productivity** – or use public policy to hasten its demise, e.g., "squeezing" agricultural surplus to invest in industry (Preobrazhensky 1921).

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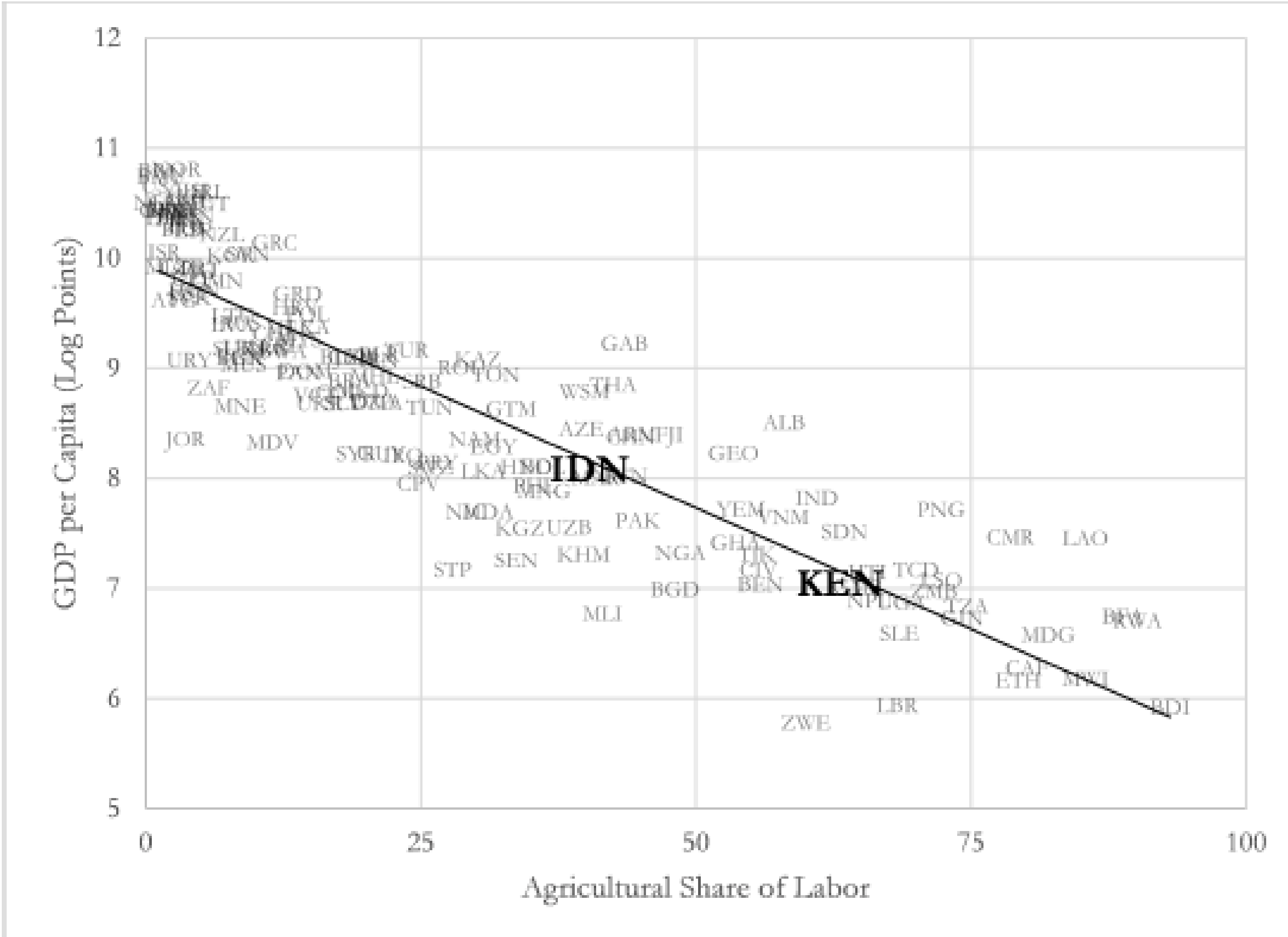
>> Is agriculture a dead-end?

Figure A1: Log GDP per Capita and Agricultural Share



Notes: Table source data is from Gollin, Lagakos, and Waugh (2014), Online Appendix Table A4. Kenya (KEN) and Indonesia (IDN) are highlighted.

Figure A2: Agricultural Productivity Gap and Agricultural Share

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The Agricultural Productivity Gap

- Are these productivity gaps causal? Or mainly a reflection of differences in worker characteristics across sectors?

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- **Gollin, Lagakos & Waugh (2014, QJE)**: focus on differences in labor quantity and quality across agriculture/non-agriculture.
- Use national accounts and some household (LSMS) data to control for differences in hours worked; average schooling / human capital; and differences in the returns to experience across sectors.

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- Use national accounts and some household (LSMS) data to control for differences in hours worked; average schooling / human capital; and differences in the returns to experience across sectors.

>> Average raw agricultural productivity gap is roughly 3.

The Adjusted Productivity Gap

- How much can differences in labor hours worked across sectors explain of the APG? A little, 1.1-1.3 on average.
- How much can differences in labor quality, as proxied by years of schooling, across sectors explain? A bit more, roughly 1.3-1.5 on average for low income countries.
- Adjust for school quality, returns to experience across sectors.

>> With adjustments, the typical APG falls to around 2.

[L]arge agriculture productivity gaps suggest... that labor is misallocated across sectors, particularly so in developing countries. By reallocating workers out of agriculture, where the value of their marginal product is low, and into other activities, aggregate output would increase even without increasing the amount of inputs employed in production. These gains could be particularly large in developing countries, where the agricultural productivity gaps and shares of employment in agriculture are largest. –Gollin, Lagakos, and Waugh (2014)

Is labor misallocated in agriculture?

- If non-agricultural work really is **twice** as productive:

1. Why don’t more workers leave the farm?
2. Why don’t more governments encourage urban relocation?
3. What frictions stand in the way of structural transformation?

Is labor misallocated in agriculture?

- If non-agricultural work really is **twice** as productive:

1. Why don’t more workers leave the farm?
2. Why don’t more governments encourage urban relocation?
3. What frictions stand in the way of structural transformation?

- Yet an important limitation of most existing work is the lack of panel data on individual productivity in different sectors.

>> Ideal “thought experiment”:

Pick people up and move them across sectors,

then measure their productivity to estimate causal gaps.

Evidence on selective migration

- **Young (2013, QJE)** documents large consumption gaps (proxied with DHS asset ownership, education) across urban/rural sectors
- Lacks earnings data, cross-sectional data on consumption proxies.
- Argues that observed gaps are “no puzzle”, due to individual worker selection: using individual birth district, individuals with more (less) schooling tend to move from rural to urban (urban to rural) areas.

Re-assessing gaps with panel data

- Can long-term panel data be used to measure productivity of the same person in agricultural and non-agricultural (as well as rural vs. urban) sectors? **Hamory, Kleemans, Li and Miguel (2020)**.
- This paper focuses on Indonesia and Kenya, which have large data sets with high individual tracking rates.

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1. Does accounting for unobserved individual heterogeneity narrow – or widen – productivity gaps?
2. How important is individual selection into migration?

Figure 1: Productivity Gap in Total Earnings

Gollin, Lagakos and Waugh (2014)

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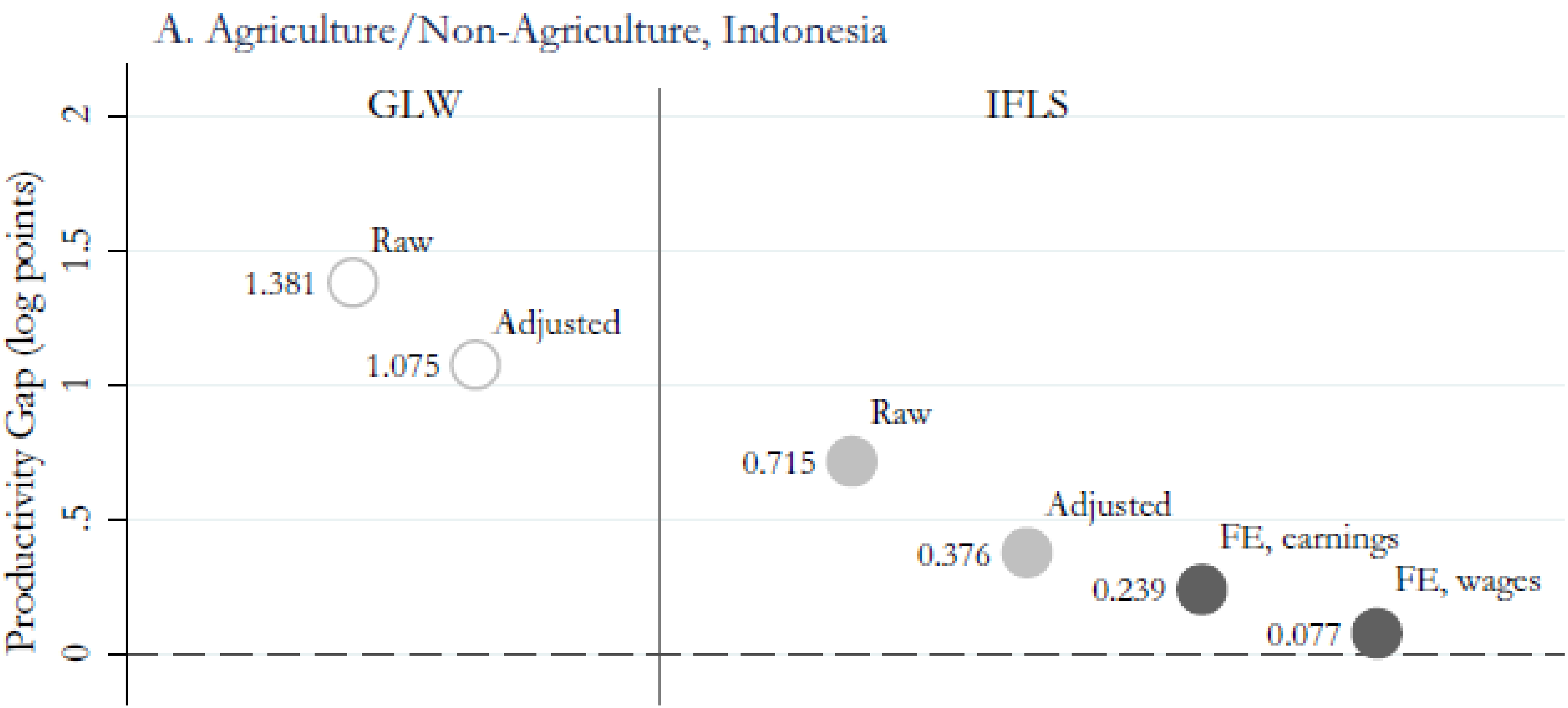

Gollin, Lagakos and Waugh (2014)

Hamory et al (2020)

Related Literature

- Methodologically related: **Hendricks and Schoellman (2018)** use panel data on earnings of international immigrants to the U.S.; including individual FE's reduces the "return" to migrating by 60%.
- Related to debate over institutions vs. human capital in development

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- McKenzie et al (2010) argue that cross-sectional estimates overstate returns to international migration (from Tonga to New Zealand), due to positive selection.
- Beegle et al (2011) on selection (by education) into migration in Tanzania and returns to migration; Munshi & Rosenzweig (2016) for India; Bryan & Morten (2017) for Indonesia and US.
- Bryan et al (2014) on male seasonal urban migration in Bangladesh

Conceptual background

- Allow sector-specific production functions, with different levels of TFP (possibly driven in part by "wedges" or other distortions).
- Income for individual i in sector s is $Y_{is} = Z_s H_i L_{is}$, where $s \in \{a, n\}$ and "a" denotes agriculture, "n" non-agriculture.

- With lower case denoting logs and stars denoting averages, the average productivity gap across sectors is:

$$y_n^* - y_a^* = (z_n - z_a) + (l_n^* - l_a^*) + (h_n^* - h_a^*)$$

$$= (\textbf{Residual productivity gap, } \boldsymbol{\beta})$$

$$+ \text{(Labor supply gap)} + \text{(Human capital gap)}$$

Conceptual background

- A more realistic view of human capital accounts for unobserved heterogeneity across individuals.
- Using the Mincerian form, let: $H_i = \exp[x_i'b + \eta_i]$, where x_i is a vector of observed characteristics (e.g., years of schooling) and η_i is unobserved individual skill.
- Log income: $y_i = z_s + 1(s{=}n)^*\beta + l_i + x_i'b + \eta_i$
- And the measured productivity gap across sectors becomes:

$$y_n^* - y_a^* = \beta + (l_n^* - l_a^*) + (x_n^* - x_a^*)'b + (\eta_n^* - \eta_a^*)$$

- OLS is biased if individual unobservables (η_i) matter; positive bias if unobservably higher ability individuals tend to be in non-agriculture.

  → Panel data estimation with individual fixed effects.

Conceptual background

- A richer formulation allows for sector specific, and time-sector specific, individual productivity shocks; related to Roy (1951).
- Let $H_{ist} = \exp[x_i{'}b + \theta_{is} + \omega_{ist}]$

where θ_{ia} (θ_{in}) is agricultural (non-agricultural) productivity, and ω_{ist} is the individual sector-specific time-varying shock.

- Panel data may allow us to account for the time-invariant individual terms by sector (θ_{ia} and θ_{in}). However, there remain important limitations: we cannot separately identify time-varying productivity, taste shocks without stronger assumptions, nor can we identify effects for those who are always in the same sector.

Conceptual background

- Natural to think **selection bias** is likely to often be positive: those with "good" productivity draws in the non-agricultural (urban) sector are observed, likely leading to upwardly biased estimates.
- Hendricks and Shoellman (2018) make the same assumption.
- (However, we cannot rule out that some with high returns cannot take up good job opportunities, say due to credit constraints.)

- Opposite bias for migrants in the other direction → bounds. I.e., estimates based on urban to rural migration: downwardly biased.

>> Are estimates based on rural-born individuals larger than those based on the urban-born?

Indonesia Family Life Survey (IFLS)

- Representative of 83% of Indonesian population (total 250m).
- **Five waves covering 27 years (1988–2015)** with less than 5% attrition across rounds.
- Current and retrospective annual data on income, employment, consumption, and location.
- 31,537 individuals giving 258,745 individual-year observations.
- 16% of individuals have separate urban, rural earnings measures; migration defined as residence for ≥6 consecutive months.

- (Note regarding generalizability: Indonesia and Kenya are quite populous countries, with ~300 million people combined, are from different world regions, and they are not outliers in the GLW data.)

Figure 2: Sample Areas

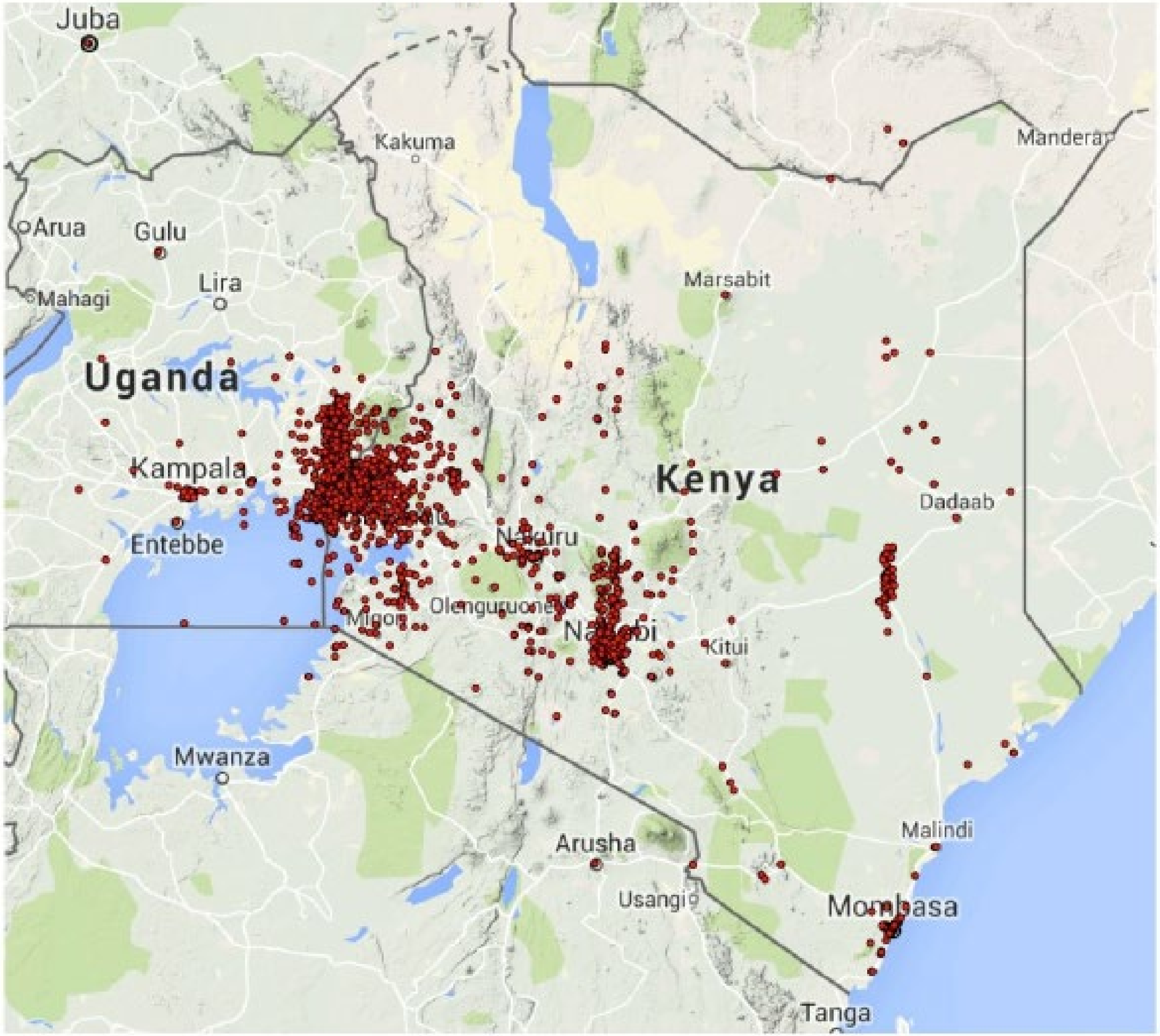
(A) Indonesia Family Life Survey

Kenya Life Panel Survey (KLPS)

- Data on nearly 9,000 individuals who attended school in Busia, Kenya and involved in two interventions (Primary School Deworming Project, Girls' Scholarship Program).

- **Three waves covering 16 years (1998–2014)** with tracking rate of 85% across rounds, including detailed retrospective income, employment, and location data at the month level.
- 23% of individuals have separate earnings measurements in urban and rural areas, where 4 consecutive months establishes "residence" (i.e., not seasonal migration).
- 54% are urban residents at some point.

(B) Kenya Life Panel Survey



Defining sector: Rural vs. agriculture

- Gollin, Lagakos & Waugh (2014) focus on the agricultural productivity gap; other studies focus on urban/rural differences.

- Present both here and show that they are closely related.
- **Agriculture / non-agriculture** employment sector: based on primary occupation (in survey), as is standard in the labor surveys.
- **Urban residence** in both Kenya and Indonesia is defined as living in a city or town (based on survey response to location type).

Earnings, wage and consumption data

- **Informal employment** is important to consider in low-income countries, and this is one reason why some are skeptical about macro estimates of sectoral productivity gaps: perhaps lots of informal or home production is just “missed” in rural areas?
- Detailed LSMS-style household surveys (like IFLS, KLPS) were designed to address these concerns.

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- Consider the sum of **labor earnings plus self-employment profits**
- Small-scale home subsistence agricultural production available for one round in Kenya; agricultural labor earnings plus commercial activity in agriculture (e.g., crop sales) always included.
- Consumption expenditures panel data for Indonesia.

Who leaves rural agriculture?

- Detailed analysis including **Ravens Progressive Matrices** cognitive scores (of fluid intelligence) for a subset of respondents in both countries.

Non-movers vs. movers in Indonesia:

Table 2: Summary Statistics

(A) Indonesia

	All N=31537	Always Rural N=11927	Rural-to-Urban Migrants N=9881	Always Urban N=7226	Urban-to-Rural Migrants N=2492	Obs
Primary Ed.	0.875	0.793	0.900	0.966	0.907	31537
	[0.330]	[0.405]	[0.300]	[0.182]	[0.291]	
Secondary Ed.	0.397	0.246	0.391	0.629	0.469	31537
	[0.489]	[0.431]	[0.488]	[0.483]	[0.499]	
College	0.109	0.051	0.101	0.202	0.148	31537
	[0.312]	[0.220]	[0.301]	[0.402]	[0.356]	
Female	0.432	0.419	0.433	0.461	0.400	31537
	[0.495]	[0.493]	[0.496]	[0.498]	[0.490]	
Raven's Z-score	0.000	-0.183	0.048	0.194	0.107	23214
	[0.923]	[0.926]	[0.917]	[0.870]	[0.926]	

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Non-movers vs. movers in Kenya:

(B) Kenya

	All N=4718	Always Rural N=1603	Rural-to-Urban Migrants N=3115	Always Urban	Urban-to-Rural Migrants	Obs
Primary Ed.	0.734	0.638	0.783			4718
	[0.442]	[0.481]	[0.412]			
Secondary Ed.	0.352	0.240	0.411			4718
	[0.478]	[0.427]	[0.492]			
College	0.035	0.012	0.046			4718
	[0.183]	[0.108]	[0.210]			
Female	0.521	0.519	0.522			4718
	[0.500]	[0.500]	[0.500]			
Raven's Z-score	0.051	-0.142	0.149			4452
	[0.985]	[0.978]	[0.974]			

Table 3: Correlates of Employment in Non-Agriculture and Urban Migration

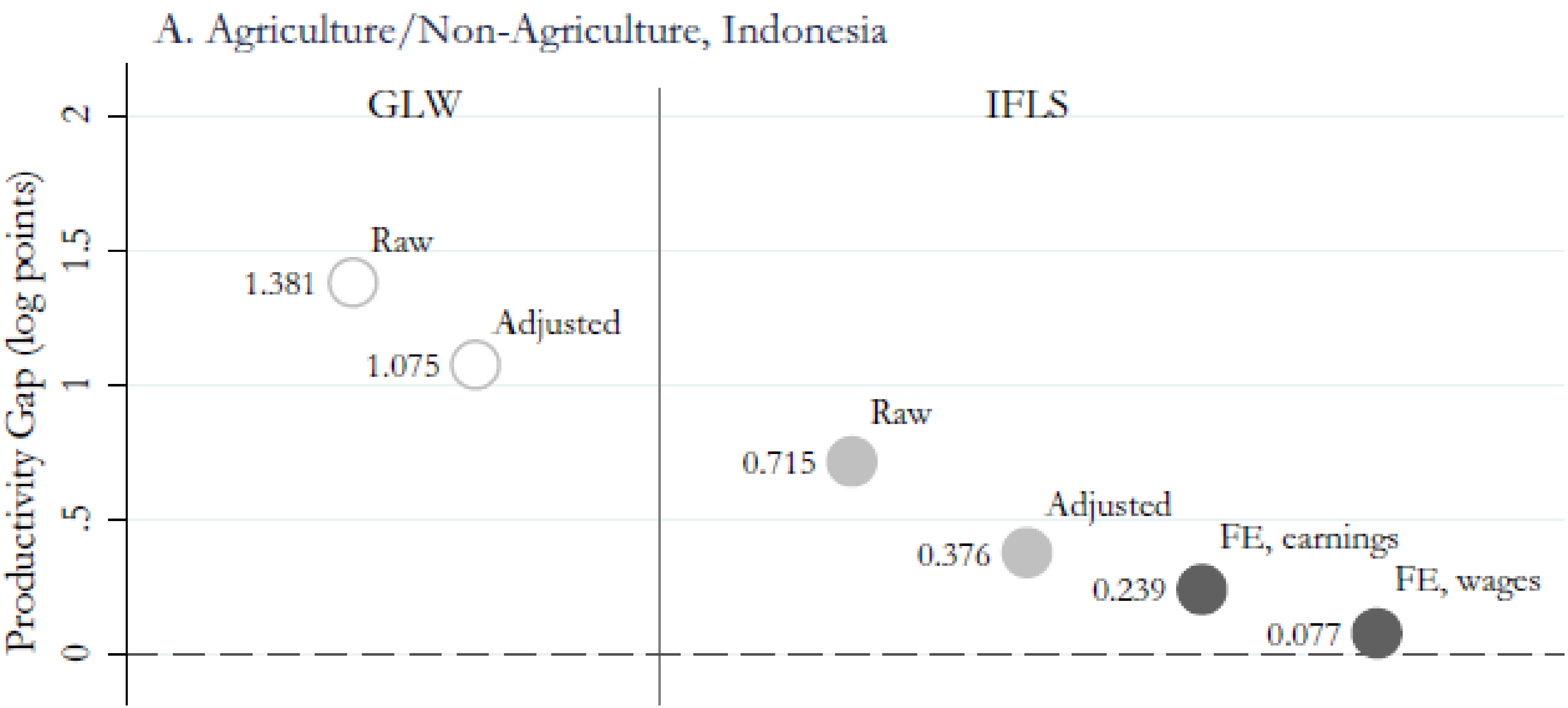
	Dependent Variable: Non-Agricultural Employment		Dependent Variable: Urban Migration	
	(1) Indonesia	(2) Kenya	(3) Indonesia	(4) Kenya
Primary Ed.	0.212***	0.103***	0.124***	0.086***
	(0.013)	(0.014)	(0.013)	(0.019)
Secondary Ed.	0.131***	0.045***	0.090***	0.099***
	(0.007)	(0.008)	(0.009)	(0.017)
College	0.051***	0.015*	0.039**	0.114***
	(0.007)	(0.008)	(0.016)	(0.028)
Female	0.082***	0.031***	0.036***	0.018
	(0.006)	(0.009)	(0.008)	(0.014)
Raven's Z-score	0.036***	0.021***	0.047***	0.031***
	(0.004)	(0.005)	(0.004)	(0.008)
Constant	0.514***	0.796***	0.305***	0.548***
	(0.013)	(0.013)	(0.012)	(0.017)
Observations	16041	4452	16041	4452

Notes: See Table 2 for sample restrictions and row variable definitions. The dependent variable in the first two columns is an indicator for being ever being employed in non-agriculture and in the last two columns the dependent variable is an indicator for being an urban migrant. All regressions are estimated on individuals who are born rural. Robust standard errors reported below in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Productivity gap estimates

- Present results for (1) Non-agriculture/agriculture, and (2) Urban/rural productivity gaps, for both Indonesia and Kenya.

Figure 1: Productivity Gap in Total Earnings



Gollin, Lagakos and Waugh (2014)

Hamory et al (2020)

Table 4: Non-Agricultural/Agricultural Gap in Earnings

(A) Indonesia

	Dependent variable: Log Earnings								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) Log Wage	(9) Log Real Wage
Non-agricultural employment	0.715***	0.604***	0.376***	0.364***	0.233***	0.299***	0.239***	0.077***	0.075***
	(0.013)	(0.012)	(0.012)	(0.014)	(0.018)	(0.018)	(0.017)	(0.020)	(0.020)
Log hours		0.564***	0.434***	0.454***	0.290***		0.350***		
		(0.016)	(0.015)	(0.017)	(0.038)		(0.019)		
Log hours squared		−0.023***	−0.009***	−0.013***	0.019***		−0.007**		
		(0.003)	(0.003)	(0.003)	(0.007)		(0.003)		
Female			−0.440***	−0.439***	−0.475***				
			(0.010)	(0.012)	(0.028)				
Years of education			0.015***	0.002	0.027***				
			(0.004)	(0.005)	(0.009)				
Years of education squared			0.004***	0.004***	0.003***				
			(0.000)	(0.000)	(0.001)				
Normalized Ravens				0.065***					
				(0.006)					
Normalized Ravens squared				0.015***					
				(0.005)					
Individual fixed effects	N	N	N	N	N	Y	Y	Y	Y
Time fixed effects	N	Y	Y	Y	Y	Y	Y	Y	Y
Switchers only					Y				
Number of observations	258745	258745	258745	196354	48479	258745	258745	258745	258580
Number of individuals	31537	31537	31537	23214	3907	31537	31537	31537	31530

Figure 1: Productivity Gap in Total Earnings

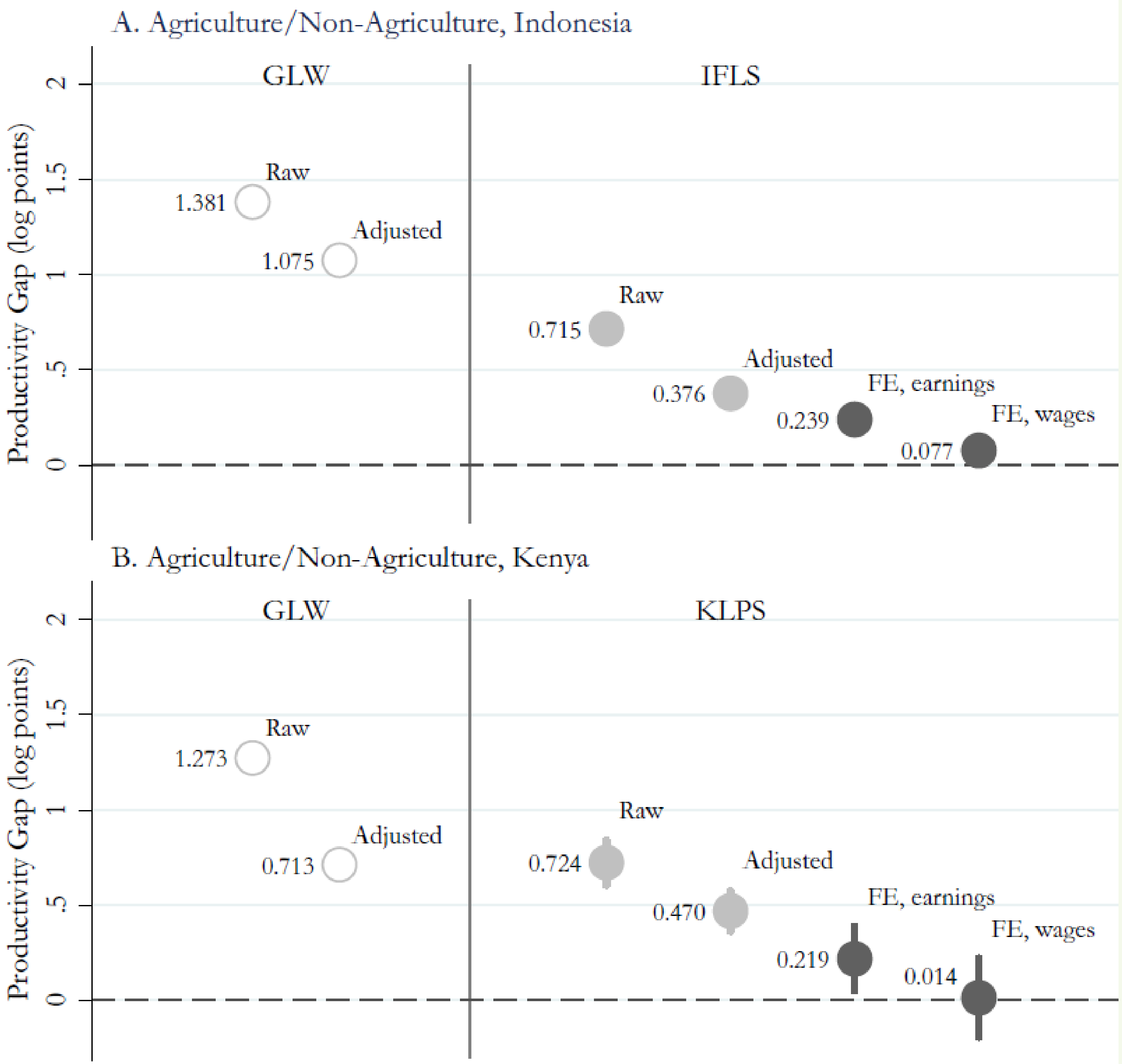


Figure 1: Productivity Gap in Total Earnings

Tables

Productivity gap estimates

- Present results for (1) Non-agriculture/agriculture, and (2) Urban/rural productivity gaps, for both Indonesia and Kenya.

>> Main finding: accounting for individual heterogeneity reduces measured productivity gaps across sectors by roughly 70 to 90%.

Additional productivity gap estimates

- Rural born versus urban born individuals (Table 6)
- Alternative agriculture productivity measures (Table A10)
- Estimates for consumption in IFLS (Table A19)
- Distribution of rural, urban productivities (Figure A8)
- Dynamic effects over 5 years (Figure 3)
- Big city effects (Table A23)
- Discussion and broader issues (Conclusion)

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Consumption

Table 6: Gap in Earnings, Indonesia
For Individuals Born Rural and Urban

(A) Individuals born in rural areas

	Dependent variable: Log Earnings		
	(1)	(2)	(3) Log Wage
Urban	0.438***	0.210***	0.039**
	(0.014)	(0.011)	(0.017)
Individual fixed effects	N	N	Y
Control variables and time FE	N	Y	Y
Number of observations	186889	186889	186889
Number of individuals	21764	21764	21764

(B) Individuals born in urban areas

	Dependent variable: Log Earnings		
	(1)	(2)	(3) Log Wage
Urban	0.320***	0.146***	0.013
	(0.027)	(0.021)	(0.027)
Individual fixed effects	N	N	Y
Control variables and time FE	N	Y	Y
Number of observations	71354	71354	71354
Number of individuals	9662	9662	9662

Col. 3 diff p-value =0.21

Table A10: Robustness to Alternative Agricultural Productivity Measures

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(A) Indonesia

Definition of Agriculture	Productivity Measure Includes... Formal Wages	Self-Employed Profits	Dependent variable: Log Wage
Majority of hours in agriculture			
Main Estimation	✓	✓	0.077***
			(0.020)
Any hours in agriculture	✓	✓	0.040**
			(0.018)
All hours in agriculture	✓	✓	0.098***
			(0.019)
Majority of hours in agriculture	✓		-0.019
			(0.024)
Self-employment only		✓	0.128***
			(0.030)

Effects: -0.02 to 0.13

(B) Kenya

Definition of Agriculture	Productivity Measure Includes... Formal Wages	Self-Employed Profits	Dependent variable: Log Wage
Majority of hours in agriculture			
Main Estimation	✓	✓	0.014
			(0.106)
Any hours in agriculture	✓	✓	0.057
			(0.096)
All hours in agriculture	✓	✓	0.010
			(0.108)
Majority of hours in agriculture	✓		0.098
			(0.120)
Self-employment only		✓	0.031
			(0.177)

Effects: 0.01 to 0.10

Productivity versus living standards

- Productivity and “utility” may diverge for many reasons, including price differences across regions, as well as amenities.
- There could be considerable individual heterogeneity in the taste for rural versus urban amenities, e.g., comforts of home, ethnic homogeneity, safety, better informal insurance, etc. in rural areas versus cosmopolitan cities with better public goods and more excitement (but downsides too – more crime!).

- A more direct test of differences in living standards uses LSMS-style **consumption expenditure** panel data for Indonesia.
- Additional advantage: helps accounts for total earnings including unemployment, job rationing, other labor market frictions.

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Born urban/rural

Table A19: Gaps in Consumption

(A) Indonesia

	Dependent variable: Log Consumption					
	(1)	(2)	(3)	(4)	(5)	(6)
Non-agricultural employment	0.441***	0.223***	0.076***			
	(0.007)	(0.006)	(0.010)			
Urban				0.379***	0.183***	0.050***
				(0.006)	(0.006)	(0.009)
Individual fixed effects	N	N	Y	N	N	Y
Control variables and time FE	N	Y	Y	N	Y	Y
Number of observations	77303	77303	77303	77303	77303	77303
Number of individuals	34143	34143	34143	34143	34143	34143

Effects: 0.076 and 0.050

Characterizing sector-specific productivity

- It is possible to estimate separate individual productivity fixed effects in both urban and rural areas, θ_{iu} and θ_{ir} .
- The relationship between these quantities appears in theoretical treatments of selective migration (Lagakos and Waugh 2013).

- Interpretation of this relationship requires some caution due to possible measurement error / attenuation, the fact that they are jointly estimated, and the fact that productivity is only observed in both sectors for some.

Figure A8: Joint Distribution of Rural and Urban Productivities

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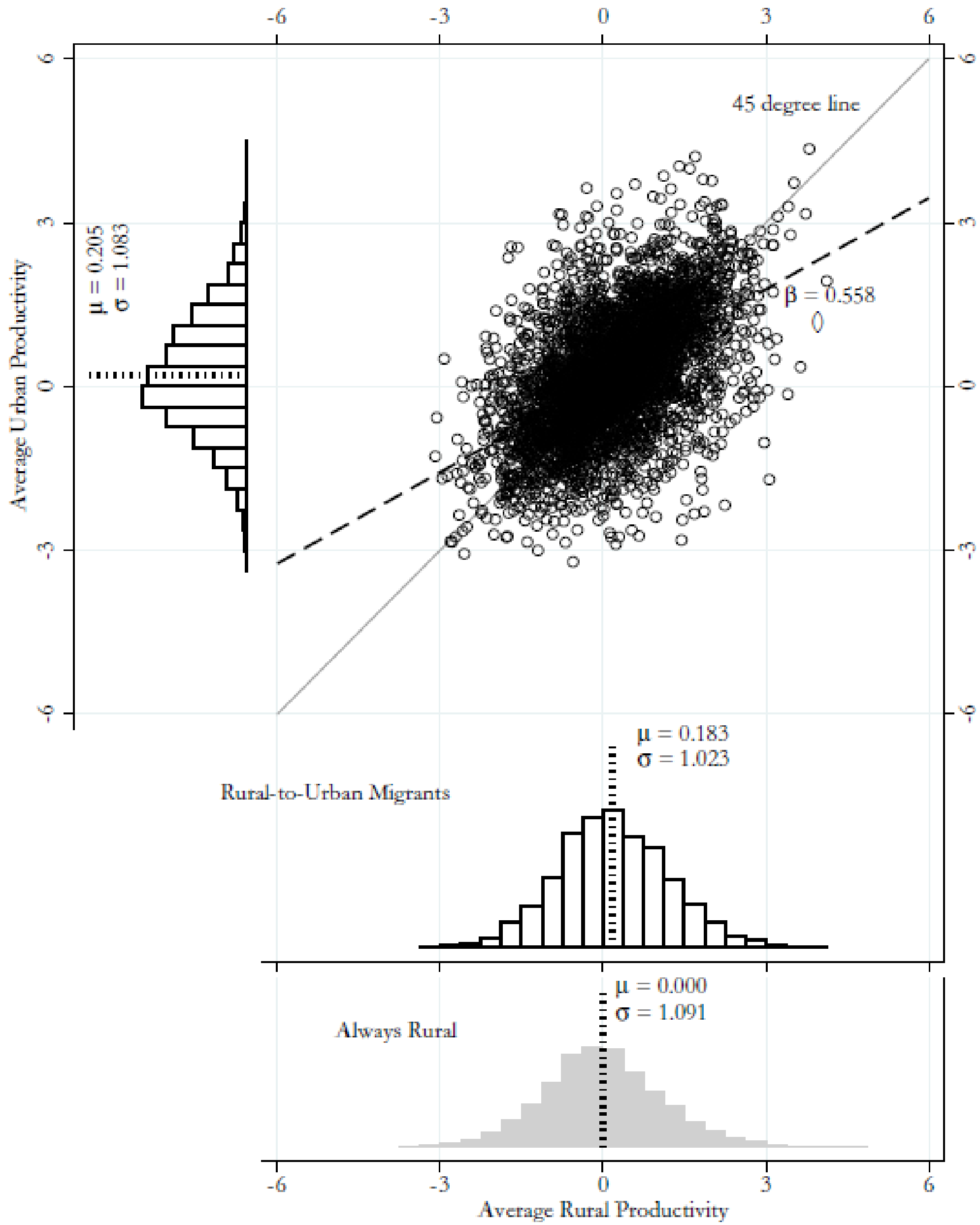
(A) Indonesia (Born Rural)

Urban effect:
0.205 – 0.183
= +0.022



Selection effect:
0.183 – 0.000
= +0.183

Dynamic and city-specific effects

- Using data from Spain, De la Roca and Puga (2016) show job experience in big cities is especially valuable at boosting labor productivity over time.

- Are there “big city” effects of this kind (e.g., Nairobi), as well as **dynamic effects** (up to five years after an urban move)?

Dynamic effects over 5 years:

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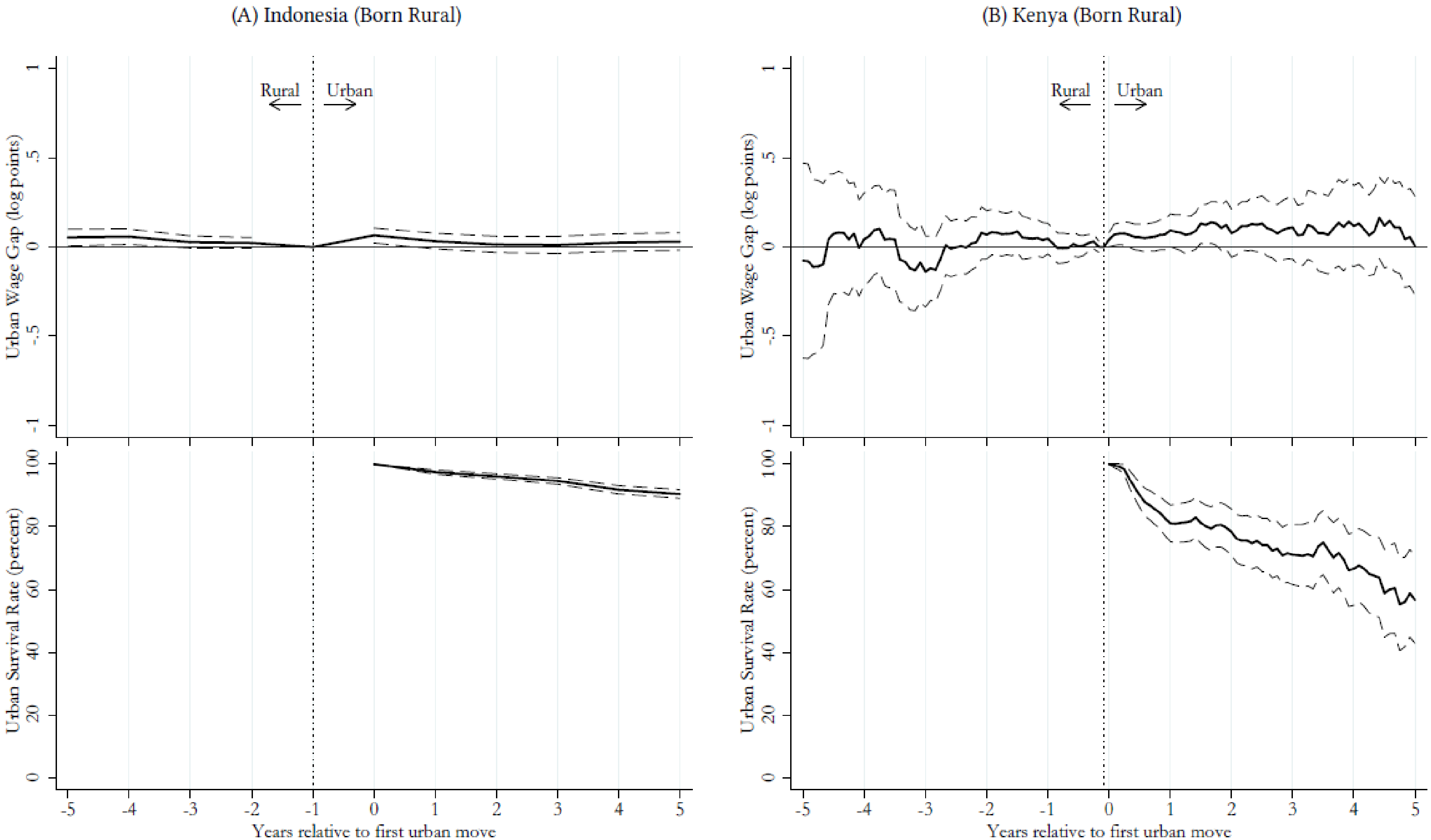
Figure 3: Event Study of Urban Migration



Urban Wage Gap

Urban "Survival" Rate

Indonesia

Kenya

Table A23: Urban/Rural Gap in Wages for Top 5 Cities

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(A) Indonesia

	Dependent variable: Log Wages			
	(1)	(2)	(3)	(4)
Urban	0.345***	0.291***	0.074***	0.032**
	(0.011)	(0.012)	(0.011)	(0.014)
Jakarta (population 10 million)		0.293***	0.315***	0.025
		(0.020)	(0.017)	(0.038)
Surabaya (population 2.8 million)		−0.012	−0.003	0.012
		(0.056)	(0.047)	(0.110)
Bandung (population 2.6 million)		0.239***	0.153***	0.094
		(0.060)	(0.047)	(0.110)
Medan (population 2.5 million)		0.286***	0.269***	−0.022
		(0.048)	(0.045)	(0.139)
Bekasi (population 2.5 million)		0.682***	0.477***	0.151*
		(0.060)	(0.055)	(0.086)
Individual fixed effects	N	N	N	Y
Control variables and time FE	N	N	Y	Y
Number of observations	258745	258745	258745	258745
Number of individuals	31537	31537	31537	31537

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(B) Kenya

	Dependent variable: Log Wages			
	(1)	(2)	(3)	(4)
Urban	0.484***	0.309***	0.272***	0.048
	(0.036)	(0.055)	(0.050)	(0.060)
Nairobi (population 3.4 million)		0.280***	0.262***	0.139**
		(0.056)	(0.050)	(0.058)
Mombasa (population 1.2 million)		0.274***	0.262***	0.263***
		(0.074)	(0.069)	(0.088)
Kisumu (population 0.4 million)		−0.065	−0.006	−0.140
		(0.127)	(0.119)	(0.106)
Nakuru (population 0.3 million)		0.232**	0.156*	0.201
		(0.109)	(0.089)	(0.149)
Eldoret (population 0.3 million)		0.066	0.026	−0.221*
		(0.143)	(0.146)	(0.127)
Individual fixed effects	N	N	N	Y
Control variables and time FE	N	N	Y	Y
Number of observations	130322	130322	130322	130322
Number of individuals	4718	4718	4718	4718

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Dynamic and city-specific effects

- Using data from Spain, De la Roca and Puga (2016) show job experience in big cities is especially valuable at boosting labor productivity over time.

- Are there “big city” effects of this kind (e.g., Nairobi), as well as **dynamic effects** (up to five years after an urban move)?

>> No evidence of dynamic effects,

mixed evidence on big city effects (only in Kenya).

Discussion

- Returning to the initial questions:

1. **Are agricultural productivity gaps causal**, or mainly a reflection of differences in worker characteristics across sectors?

Discussion

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1. **Are agricultural productivity gaps causal**, or mainly a reflection of differences in worker characteristics across sectors?

- Careful macro-empirical work is unable to "knock out" the agricultural productivity gap (Gollin, Lagakos and Waugh 2014)
- But accounting for unobserved individual heterogeneity greatly reduces gaps, often close to zero (this paper)

>> The large share of workers who choose to remain in rural agriculture may not be such a puzzle after all.

Discussion

- Returning to the initial questions:

2. **Is "re-allocating" labor out of agriculture** likely to be an attractive public policy, in terms of boosting aggregate living standards?

- Probably not, at least in the short run. Individuals who move out of rural agriculture in Indonesia and Kenya experience modest wage gains on average (although some individuals do gain more).

Discussion

- Returning to the initial questions:

2. **Is "re-allocating" labor out of agriculture** likely to be an attractive public policy, in terms of boosting aggregate living standards?

- Probably not, at least in the short run. Individuals who move out of rural agriculture in Indonesia and Kenya experience modest wage gains on average (although some individuals do gain more).

- A related historical policy: 1973 **"Operation Vijiji"** forced households into central villages and towns in Tanzania, with negative economic, social and political consequences.

Discussion

- Important caveat to our analysis: migration is non-random
- Comparison: **Bryan et al (2014)** subsidize seasonal (male) urban migration in Bangladesh, very useful experimental variation
- Moderate consumption gains among sending household members (~30% IV) and perhaps earnings gains (~25% ITT, not significant)

- Are these findings in conflict with ours? Probably not:

1. Effect magnitudes far closer to ours than to GLW
2. Identify different local average treatment effects
3. More speculatively, seasonal returns during the agricultural low season for males may be an **upper bound** on gains to permanent urban migration

Broader Issues

- Could there be something consequential about the gap that this study is missing?

- For instance, perhaps productivity gains kick in over very long time horizons (>5 years)? Or effects on the **next generation**? (Table A17) Do individuals who grow up in urban areas become more skilled or productive? E.g., better schools, intellectual stimulation

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- Alternatively (and not mutually exclusively), wave after wave of highly selected two-way migration flows between urban and rural areas, combined with partial heritability of cognitive ability, may have **reshaped the underlying ability distributions** across sectors.

Broader Issues

- A relatively small agricultural productivity gap does **not** imply that African agriculture is highly productive:
- Labor productivity in Sub-Saharan Africa remains the lowest in the world in **both** the agricultural and non-agricultural sectors

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- A relatively small agricultural productivity gap does **not** imply that African agriculture is highly productive:
- Labor productivity in Sub-Saharan Africa remains the lowest in the world in **both** the agricultural and non-agricultural sectors

- To what extent should investments in agriculture be prioritized (or de-emphasized) going forward?
- Is there greater potential for future **urban productivity growth**?
- Potentially very high returns to developing technologies and policies that boost productivity overall, and in particular those that allow African farmers to **adapt to a warming climate**.

END – EXTRA SLIDES

Table 1: Non-Agriculture/Agriculture and Urban/Rural

(A) Indonesia (Main Analysis Sample)

	Rural	Urban	Total
Agriculture	46.9%	10.7%	29.4%
Non-Agriculture	53.1%	89.%3	70.6%
Number of Observations	133,726	125,019	258,745

(B) Kenya (Main Analysis Sample)

	Rural	Urban	Total
Agriculture	26.0%	5.4%	15.2%
Non-Agriculture	74.0%	94.6%	84.8%
Number of Observations	61,750	68,572	130,322

(C) Kenya (12 Months with Subsistence Agricultural Module)

	Rural	Urban	Total
Agriculture	59.1%	9.1%	40.6%
Non-Agriculture	40.9%	90.9%	59.4%
Number of Observations	27,301	16,029	43,330

Table 4: Non-Agricultural/Agricultural Gap in Earnings

(B) Kenya

	Dependent variable: Log Earnings								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) Log Wage	(9) Log Real Wage
Non-agricultural employment	0.724***	0.471***	0.470***	0.479***	0.272***	0.333***	0.219**	0.014	0.003
	(0.060)	(0.056)	(0.054)	(0.055)	(0.094)	(0.086)	(0.086)	(0.106)	(0.106)
Log hours		0.350**	0.254*	0.268*	0.283		0.218		
		(0.170)	(0.152)	(0.153)	(0.323)		(0.242)		
Log hours squared		0.014	0.017	0.016	0.008		0.015		
		(0.019)	(0.017)	(0.017)	(0.039)		(0.026)		
Female			−0.491***	−0.467***	−0.535***				
			(0.034)	(0.036)	(0.110)				
Years of education			0.007	−0.002	−0.012				
			(0.035)	(0.036)	(0.117)				
Years of education squared			0.004**	0.004**	0.004				
			(0.002)	(0.002)	(0.007)				
Normalized Ravens				0.072***	0.011				
				(0.021)	(0.069)				
Normalized Ravens squared				−0.045**	−0.138**				
				(0.018)	(0.070)				
Individual fixed effects	N	N	N	N	N	Y	Y	Y	Y
Time fixed effects	N	Y	Y	Y	Y	Y	Y	Y	Y
Switchers only					Y				
Number of observations	130322	130322	130322	124481	14345	130322	130322	130322	130251
Number of individuals	4718	4718	4718	4452	324	4718	4718	4718	4715

Table 5: Urban/Rural Gap in Earnings

(A) Indonesia

	Dependent variable: Log Earnings								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) Log Wage	(9) Log Real Wage
Urban	0.502***	0.422***	0.225***	0.200***	0.090***	0.043***	0.041***	0.033**	−0.060***
	(0.011)	(0.011)	(0.009)	(0.011)	(0.015)	(0.013)	(0.012)	(0.014)	(0.014)
Log hours		0.536***	0.414***	0.433***	0.373***		0.343***		
		(0.016)	(0.015)	(0.016)	(0.031)		(0.019)		
Log hours squared		−0.012***	−0.002	−0.005*	0.007		−0.005		
		(0.003)	(0.003)	(0.003)	(0.006)		(0.003)		
Female			−0.400***	−0.396***	−0.377***				
			(0.010)	(0.012)	(0.021)				
Years of education			0.020***	0.007	0.014*				
			(0.004)	(0.005)	(0.008)				
Years of education squared			0.004***	0.004***	0.004***				
			(0.000)	(0.000)	(0.000)				
Normalized Ravens				0.071***					
				(0.007)					
Normalized Ravens squared				0.013***					
				(0.005)					
Individual fixed effects	N	N	N	N	N	Y	Y	Y	Y
Time fixed effects	N	Y	Y	Y	Y	Y	Y	Y	Y
Switchers only					Y				
Number of observations	258745	258745	258745	196354	69519	258745	258745	258745	258580
Number of individuals	31537	31537	31537	23214	5683	31537	31537	31537	31530

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(B) Kenya

	Dependent variable: Log Earnings								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) Log Wage	(9) Log Real Wage
Urban	0.778***	0.660***	0.604***	0.603***	0.297***	0.273***	0.219***	0.123***	0.046
	(0.035)	(0.034)	(0.032)	(0.032)	(0.050)	(0.042)	(0.040)	(0.043)	(0.043)
Log hours		0.348**	0.259*	0.262*	0.309		0.238		
		(0.157)	(0.143)	(0.145)	(0.334)		(0.242)		
Log hours squared		0.009	0.014	0.014	0.013		0.013		
		(0.017)	(0.016)	(0.016)	(0.036)		(0.026)		
Female			−0.455***	−0.431***	−0.299***				
			(0.033)	(0.034)	(0.065)				
Years of education			−0.007	−0.012	−0.050				
			(0.033)	(0.034)	(0.057)				
Years of education squared			0.005***	0.005***	0.006**				
			(0.002)	(0.002)	(0.003)				
Normalized Ravens				0.062***	0.087**				
				(0.020)	(0.038)				
Normalized Ravens squared				−0.027	−0.007				
				(0.018)	(0.032)				
Individual fixed effects	N	N	N	N	N	Y	Y	Y	Y
Time fixed effects	N	Y	Y	Y	Y	Y	Y	Y	Y
Switchers only					Y				
Number of observations	130322	130322	130322	124481	38206	130322	130322	130322	130251
Number of individuals	4718	4718	4718	4452	1017	4718	4718	4718	4715

Figure A3: Types of Individual Agricultural Productivity Data

	Lower quality measures ←			→ Higher quality measures
(A) Indonesia				
Source of agricultural productivity and hours		**Self-employed profits (commercial and subsistence agriculture)[1]**		**Wage employment**
Individual-years in Agriculture		55,130		29,155
Individuals in Agriculture		6,867		5,666
Agriculture productivity gap (Standard error) [Individual-years]		0.128*** (0.030) [134,153]		−0.019 (0.024) [139,846]
		0.077*** (0.020) 258,745		
(B) Kenya				
Source of agricultural productivity and hours	**Less reliable individual agricultural productivity data[2]**	**Self-employed profits (subsistence agriculture)**	**Self-employed profits (commercial agriculture)**	**Wage employment**
Individual-months in Agriculture	3,507	2,331	4,225	13,754
Individuals in Agriculture	348	205	137	537
Agriculture productivity gap (Standard error) [Individual-months]		0.031 (0.177) [37,064]		0.098 (0.120) [94,653]
		0.014 (0.106) 130,322		

Table A17: Intergenerational Correlations of Cognitive Measures

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(A) Indonesia

	Dependent variable: Normalized Ravens				
	(1)	(2)	(3)	(4)	(5)
Child Covariates:					
Born Urban	0.211***	0.212***	0.146***	0.034**	0.033*
	(0.015)	(0.015)	(0.017)	(0.017)	(0.017)
Female		−0.141***	−0.141***	−0.135***	−0.134***
		(0.015)	(0.015)	(0.014)	(0.014)
Parent (Averaged) Covariates:					
Born Urban			0.207***	0.082***	0.081***
			(0.022)	(0.022)	(0.022)
Age at Birth			−0.002	−0.000	0.013*
			(0.001)	(0.001)	(0.008)
Years of Education				0.044***	0.071***
				(0.002)	(0.007)
Normalized Ravens				0.112***	0.116***
				(0.009)	(0.009)
Age, Education, and Ravens Squared	N	N	N	N	Y
Number of observations	11921	11921	11921	11921	11921

(B) Kenya

	Dependent variable: Normalized Cognitive Ability Index				
	(1)	(2)	(3)	(4)	(5)
Child Covariates:					
Born Urban	0.344***	0.345***	0.369***	0.258***	0.258***
	(0.082)	(0.082)	(0.083)	(0.085)	(0.085)
Female		0.111	0.111	0.102	0.108
		(0.070)	(0.070)	(0.069)	(0.069)
KLPS Parent Covariates:					
Female			0.271***	0.308***	0.309***
			(0.075)	(0.073)	(0.074)
Age at Birth			0.002	0.013	0.270
			(0.014)	(0.014)	(0.195)
Years of Education				0.065***	0.068
				(0.014)	(0.067)
Normalized Ravens				0.055	0.053
				(0.040)	(0.041)
Age, Education, and Ravens Squared	N	N	N	N	Y
Number of observations	864	864	864	864	864

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Table A22: Gap in Consumption for those Born in Rural and Urban Areas, Indonesia

(A) Indonesian individuals born in rural areas (Dependent variable: Log Consumption)

	Full Consumption Sample			Main Analysis Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Urban	0.351***	0.184***	0.049***	0.353***	0.187***	0.057***
	(0.008)	(0.007)	(0.010)	(0.009)	(0.008)	(0.012)
Individual fixed effects	N	N	Y	N	N	Y
Control variables and time FE	N	Y	Y	N	Y	Y
Number of observations	56248	56248	56248	47134	47134	47134
Number of individuals	23857	23857	23857	21067	21067	21067

(B) Indonesian individuals born in urban areas (Dependent variable: Log Consumption)

	Full Consumption Sample			Main Analysis Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Urban	0.252***	0.118***	0.037**	0.242***	0.110***	0.062***
	(0.015)	(0.013)	(0.019)	(0.017)	(0.014)	(0.020)
Individual fixed effects	N	N	Y	N	N	Y
Control variables and time FE	N	Y	Y	N	Y	Y
Number of observations	20864	20864	20864	18655	18655	18655
Number of individuals	10167	10167	10167	9278	9278	9278