ANNEX 4: **Methodology of Economic Impact Assessment**

Some methodological issues on programme evaluation/Impact assessment

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Content of presentation

- Introduction
- Evaluation methods
- Analytical methods
  - PScore, DID
- Data collection
  - Sampling
  - Survey
- Example of method application

Objective

- Measure the impact of a policy reform or intervention on well-defined outcome variables
- Examples:
  - Childcare subsidy – child exam results
  - Targeted training program – employment duration, earnings
  - *HPAI Outbreaks* – impact on rural household livestock income or animal vaccination behaviour

example

- Impact assessment of parents' migration on child school performance in rural China

Objective:
Measure parents' migration decision on child's exam results

Problems in programme evaluation

- Missing data problem:
  - Each person is either in the program or not (not BOTH): a child is either in a parent migrating family or non-migrating family
  - There would be no evaluation problem if we can observe the outcome for those in the program had they NOT: if we have one child's exam results in both cases- during parents migrating period and not migrating period
  - Central issue: how to construct counterfactual.

Selection Bias

- $E(Y_1|P=1) - E(Y_0|P=0)$
  - P：whether parents migrated or not，1＝yes，0＝no
  - Y_1：treated outcome
  - Y_0：untreated outcome
- Add and subtract E(Y0|P=1)，we have

$$\underbrace{\{E(Y_1|P=1) - E(Y_0|P=1)\}}_{\text{Average treatment effect on the treated}} + \underbrace{\{E(Y_0|P=1) - E(Y_0|P=0)\}}_{\text{Selection bias}}$$

If $E(Y_0|P=1) \neq E(Y_0|P=0)$：
Selection bias：$E(Y_0|P=1) - E(Y_0|P=0)$

Evaluation Methods

- Randomized experiments
- Quasi-experiments: natural experiments

Randomized experiments

- Most convincing: there's a control group that is a random subset of the eligible population
- Randomized experiment in development

  Progresa (Mexico) Vouchers for private schooling in Columbia ((Angrist et al. AER 2003)

  Merit scholarship program for girls in Kenya (Kremer, Miguel, and Thornton 2003)

  Audit program of municipal expenditures in Brazil (Finan and Feraz 2006)

Identification with a randomized experiment

- Provides the correct counterfactual
- eliminates self--selection as a source of bias
- With randomized experiments:
  - Programme impacts: $\hat{d} = E(Y \mid Treated) - E(Y \mid Control)$
  - In regression: $Y_i = \alpha + d * P_i + \varepsilon_i$
  - Drawbacks of randomized experiments

2. Quasi-experiment/Natural Experiment

- Considers policy/program itself as an experiment and try to find a comparable experiment control group
- Identification problem：selection bias
- Programme participation not random
  - Earlier example:
  - Whether a child coming from a migrating family is not random
  - intuition：There is something systematically different about a child who is from a migration family (treated) compared to a child who is from a non-migration family (control), which is correlated with counterfactual outcome
  - implication：biased impact measure

Identification strategy

- Depends on what type of data you have:
  - Singer cross-section（after programme implementation）
    - IV
    - Two-step Heckman selection estimator
    - Matching（Propensity-Score Matching ）
  - Panel data (before-after programme)/multiple cross-section
    - difference-in-differences
    - difference-in-difference matching
    - Fixed effects (> two periods)

Identification strategy(2)

- **if two groups are systematically different in characteristics, let's control for them as much as possible.**
  - Propensity score matching

    Controls for observable characteristics

    Only use outcome data for after program
  - Difference-in-differences

    differences out some unobservable characteristics

    Utilize outcome data before-after program
  - Difference-in-differences matching method

    Combines the two approaches

    Controls for observable and unobservable characteristics

Brief introduction on method

- Propensity Score Matching Method
- Difference in differences

Propensity Score Matching Method

- Idea of matching
  - Directly compares individuals with similar values of observable characteristics (X_i)
  - PSM compares individuals with similar probability of participation
    - P-score $S(X_i)=\Pr(P=1|X_i)$
    - Conditional Independence Assumption (CIA):
    - Matching in general: $(Y_0 \perp P)|X$
    - PSM: $(Y_0 \perp P)|S(X)$

More Words on PSM

- Inexact Matching
- It maps X into some lower dimension measure (index) that captures all important information in X, aka P-score
- P-score: the probability of receiving treatment conditional on entire space spanned by observables
- The P-Score Theorem: If P is randomly assigned conditional on X, then P also is randomly assigned condition on S(X).

$$(Y_{0i}, Y_{1i}) \perp P_i \mid X_i \Rightarrow (Y_{0i}, Y_{1i}) \perp P_i \mid S(X_i)$$

How PSM works

Propensity scoring:

Step 1: Estimate binary choice model that explains participation

Step 2: Obtain the predicted probability of participation “propensity score”

Step 3: Match participant and non-participant with similar propensity score

Step 4: Compare the weighted averages

Balancing property check of P-Score： stop adjusting the logit/probit model when the X’s are similar for i with similar P-score

- Stratify sample into quintile blocks based on predicted p-score
- Within each quintile, compare $\bar{X}_{P=0}, \bar{X}_{P=1}$, test the difference using t-test
- If all tests (>95% of tests) are insignificant, then conclude that the Logit/Probit function is “balancing” the observables (X), that is, statistically indistinguishable
- If covariate k in particular is not balanced for small blocks, divide them into smaller blocks and reevaluate
- If covariate k is not balanced for all blocks, modify the functional form by adding interactions or higher order polynomials in covariate k
- Stop change function form when you fail to reject more than 95% of the time

Matching method

- One-to-one matching
  - Nearest neighbour matching
    - With/without replacement
  - Caliper matching: avoids “bad” matching by setting maximum distance allowed (2-5%)
- One-to-multiple matching
  - Kernel and local linear matching (non-parametric parametric methods)
    - weights depend on the distance between each comparison group observation and the participant observation for which the counterfactual is being constructed

Advantages and limitations

- Advantages of matching (vs. linear regressions)
  - Clarifies whether or not comparable untreated observations are available for each treated observation
  - avoids identifying effects solely by projections into regions where there are bad or no matches
  - Larger weights on untreated observations similar to each treated units when calculating the expected counterfactual for each treated observation (OLS uses all untreated units)
- Limitation
  - CIA: Assumes that participation and outcome are based on observable characteristics (*Xi*)
    - Might not be able to find the right counterfactual for all participants
    - Requires lots of variables

Difference In Differences

- Compares before--after changes of participants vs. before--after change of non--participants
- Any common trends get differenced out.
- limitation：
  - only *common* trends between two groups get differenced out
  - We control for base value of *Yi*, observables, and village fixed effects

$$\Delta Y_i = \alpha + dP_i + \beta_{Y_{i0}} Y_{i0} + \beta_{X_{i0}} X_{i0} + \gamma_{town} + \varepsilon_i$$
$$where$$
$$\Delta Y_i = Y_{i1} - \Delta Y_{i0}$$

Two commonly used DID methods

- Level Form: $Y_{it} = \mu + \beta X_i + \alpha P_{i1} + \delta T + \gamma P_{it} + \varepsilon_{it}$
- Differencing Form: $\Delta Y_i = \mu + \beta X_i + \alpha D_{i1} + (\varepsilon_{i1} - \varepsilon_{i0})$

$$where$$
$$\Delta Y_i = Y_{i1} - \Delta Y_{i0}$$

  - X is a vector of covariates
  - P_{i1}=1 if t=1 (post-program) and the pupil is a "treated"
  - T=1 if t=1(post-program)
  - P_{it}=1 if the pupil is a "treated"

Two basic assumptions of DID

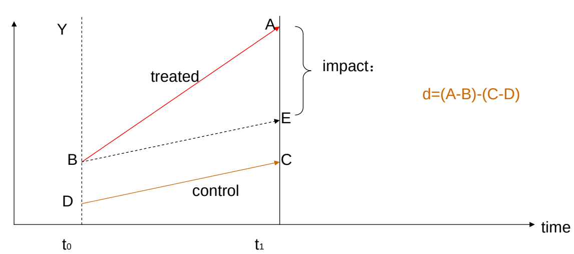
- unobserved differences does not change over time, in other words, treatment group and control group have the same trend
- Before treatment, the basic characteristics of the two groups are similar in terms of the mean。

Problems with DID

- You can still have selection on observables. Potentially, you could have
  - Omitted variable bias
  - Incorrect functional form (matching methods might be able t deal with this type of problem)
- You can still have selection on unobservables
  - Correlation in unobservables that determine program participation
  - Policy endogeneity: policy adoption is correlated with province-level trends in outcome or expectations about outcome. (need IV)
- Inference problem: DID model uses panel data, we know panel data's OLS standard error is likely to be too low, i.e., t=2.00 might be too loose, you mistakenl reject H_0.

Difference in differences

	After	before	after－before
participation	A	B	A-B
control	C	D	C-D
			d=(A-B)-(C-D)



Data collection

- Sampling
- Survey instruments

Sampling

- To select samples with representativeness
- To include different population groups
  - Participating groups
  - Control groups

Survey

- Information for different periods
  - Before - after
- Information for different groups
  - Participating – non-participating

Example of impact assessment

- Impact of parents migration on child grades

Migration, Mentoring and Mothers: The Effect of Migration on Children' Educational Performance in Rural China

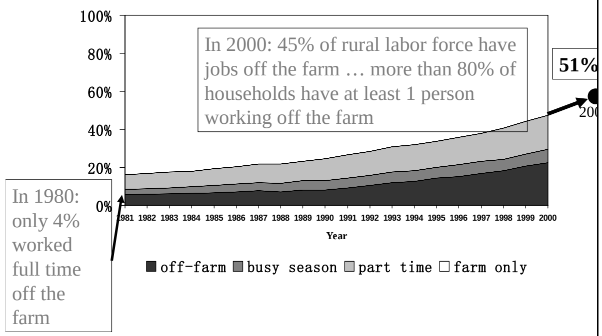
Introduction

Migration is one of the main ways of alleviating poverty in developing countries

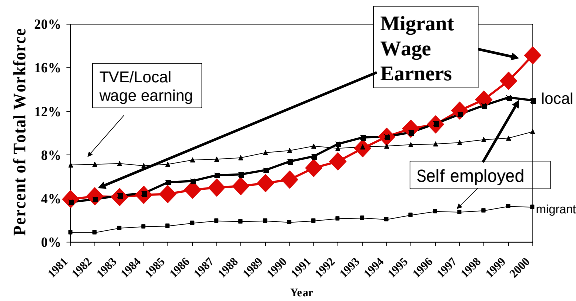
Migration itself, however, is not costless.

- For example: There may be an adverse effect of migration on the educational achievement of the children of migrants (McKenzie et al. on Mexico)

Overall Increase in Off-farm Work



Migration-fastest growing segment



Summary: Migration in China

- **Migration is rising fast, surpassing 100 million individuals (deBrauw et al., 2002)**
- **Migrants also are moving further away from home and leaving for a longer period of time (Rozelle et al., 1999).**
- **Most of China's migration is by individuals instead of entire households, in most cases the school-aged children of the migrant parents are being left.**

Results from current literature

- **School performance of the migrant children is being adversely affected by migration since parental care falls with migration (Wang and Wu, 2003; Tan and Wang, 2004; Li, 2004; Zhou and Wu, 2004).**

- **These results are all based on casual observation**
- **Are they true?**
- **Is there anything about migration that can offset this effects?**

Objectives

Examine the effect of migration activities of men and women on the educational performance of their children.

- Compare the distribution of children's scores for different types of rural households and describe how the grades vary over time.
- Examine whether migration negatively affects the school grades of rural children.
- Explore how migration will affect children's educational performance in different types of households in terms of wealth or demographic composition.

Data

- A data set collected in 2006, with information of changes in school performance of children before and after their parents outmigrated.

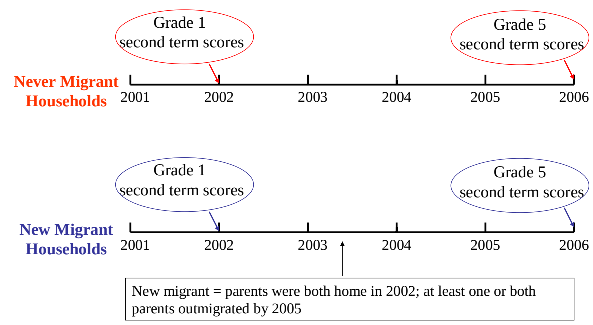
• 1649 fifth grade students in 36 primary schools in 6 counties in Shaanxi province

• Random sample of counties and schools within the counties and classes within the schools … but surveyed ALL students within each class …

Two Key Variables

- Grades of school achievement
  - math and Chinese language scores
  - scores from 2001/2 (first grade) to 2005/6 (fifth grade)
    - From records kept by students + schools
  - standardized scores (second term scores)
    [all scores from standardized tests corrected by joint grading panel of teachers]
- Migration status
  - migration histories of each parent between 2002 and 2006

Time lines of academic calendars from 2001/2 to 2005/6



Methodology (1)

Difference in Difference (DID)

Model (1), Restricted & Unadjusted: $\Delta Score_i = \alpha + \delta MIG_i + \varepsilon_i$

Model (2), Unrestricted & Unadjusted: $\Delta Score_i = \alpha + \delta MIG_i + \gamma Score\_02_i + \varepsilon_i$

Model (3), Restricted & Adjusted: $\Delta Score_i = \alpha + \delta MIG_i + \beta X_i + \varepsilon_{i,}$

Model (4), Unrestricted & Adjusted: $\Delta Score_i = \alpha + \delta MIG_i + \gamma Score\_02_i + \beta X_i +$

where, i is an index for the student, $\Delta Score_i$ is the change of the second term score student i between 2002 and 2006 (that is the final grade from the fifth grade minus the fin grade from the first grade); MIG_i is the treatment variable (which makes δ the parameter interest). Finally, the term $\mathbf{X}_i$ is a vector of covariates that are included to capture the characteristics of students, parents and households and also includes a set of 12 town indicator or dummy variables.

Our equation of choice (the full model)

- Model (4),
- Unrestricted & Adjusted:

$$\Delta Score_i = \alpha + \delta MIG_i + \gamma Score\_02_i + \beta X_i + \varepsilon_i$$

Methodology (2)

- Propensity Score Matching (PSM)

----Basic matching

----Multi-dimensional matching

- Difference in Difference Matching (DDM)

----Basic matching

----Multi-dimensional matching

Results

- DD results
- PSM results
- DDM results

Table 2. DD Regression Results Analyzing the Effect of Migration on School Performance of Students in China

	Treatment Variable (MIG_i)[b]	(1) Restricted & Unadjusted	(2) Unrestricted & Unadjusted	(3) Restricted & Adjusted[c]	(4) Unrestricted & Adjusted[c]
	Dependent Variable = Changes in Second Term Test Scores between 2002 and 2006 ($\Delta Score$)				
(1)	*Any_Parent_Migrated*	3.183	2.327	2.169	1.164
		(3.72)***	(3.03)***	(2.58)**	(1.65)*
	Characteristics of the students in 2002				
(2)	Student score in the second term in 2002 (Full score is 100)		-0.460		-0.627
			(14.93)***		(18.04)***
(3)	Gender dummy (=1 if male and 0 if female)			0.826	-0.383
				(1.28)	(0.75)
(4)	Age of the student in 2002 (Years)			0.097	-1.322
				(0.26)	(4.39)***
(5)	Cadre dummy (=1 if the student was a student cadre in 2002 and 0 if not)			-2.754	1.168
				(3.83)***	(1.93)*
(6)	Mentor dummy (=1 if the student had a mentor in 2002)			-1.051	-0.972
				(0.99)	(1.26)
(7)	Sibling dummy (=1if the student had no siblings in 2002)			0.438	0.443
				(0.55)	(0.71)
	Characteristics of the parents in 2002				
(8)	Age of the father (Years)			-0.066	-0.053
				(0.85)	(0.85)
(9)	Level of education of the father (Years of schooling)			-0.200	-0.044
				(1.06)	(0.35)
(10)	Level of education of the mother (Years of schooling)			0.114	0.274
				(0.77)	(2.39)**
	Characteristics of the household in 2002				
(11)	Size of total household land holding in 2002 (mu)			0.031	0.037
				(0.36)	(0.57)
(12)	Number of household members in 2002 (Person)			0.078	0.251
				(0.25)	(1.01)
(13)	House value dummy (=1 if the house is worth more than 5000 yuan)			0.056	-0.037
				(0.08)	(0.07)
(14)	Number of Observations	1575	1575	1549	1549
(15)	R-squared	0.01	0.27	0.10	0.43

Table 2. DD Regression Results Analyzing the Effect of Migration on School Performance of Students in China

Treatment Variable (MIG_i)	(1) Restricted & Unadjusted	(2) Unrestricted & Unadjusted	(3) Restricted & Adjusted	(4) Unrestricted & Adjusted
Dependent Variable = Changes in Second Term Test Scores between 2002 and 2006 ($\Delta Score$)				
Any_Parent_Migrated	3.183	2.327	2.169	1.164
	(3.72)***	(3.03)***	(2.58)**	(1.65)*

Table 2. DD Regression Results Analyzing the Effect of Migration on School Performance of Students in China

	Treatment Variable (MIG_i)[b]	(1) Restricted & Unadjusted	(2) Unrestricted & Unadjusted	(3) Restricted & Adjusted[c]	(4) Unrestricted & Adjusted[c]
	Dependent Variable = Changes in Second Term Test Scores between 2002 and 2006 ($\Delta Score$)				
(1)	*Any_Parent_Migrated*	3.183	2.327	2.169	1.164
		(3.72)***	(3.03)***	(2.58)**	(1.65)*
	Characteristics of the students in 2002				
(2)	Student score in the second term in 2002 (Full score is 100)		-0.460		-0.627
			(14.93)***		(18.04)***
(3)	Gender dummy (=1 if male and 0 if female)			0.826	-0.383
				(1.28)	(0.75)
(4)	Age of the student in 2002 (Years)			0.097	-1.322
				(0.26)	(4.39)***
(5)	Cadre dummy (=1 if the student was a student cadre in 2002 and 0 if not)			-2.754	1.168
				(3.83)***	(1.93)*
(6)	Mentor dummy (=1 if the student had a mentor in 2002)			-1.051	-0.972
				(0.99)	(1.26)
(7)	Sibling dummy (=1if the student had no siblings in 2002)			0.438	0.443
				(0.55)	(0.71)
	Characteristics of the parents in 2002				
(8)	Age of the father (Years)			-0.066	-0.053
				(0.85)	(0.85)
(9)	Level of education of the father (Years of schooling)			-0.200	-0.044
				(1.06)	(0.35)
(10)	Level of education of the mother (Years of schooling)			0.114	0.274
				(0.77)	(2.39)**
	Characteristics of the household in 2002				
(11)	Size of total household land holding in 2002 (mu)			0.031	0.037
				(0.36)	(0.57)
(12)	Number of household members in 2002 (Person)			0.078	0.251
				(0.25)	(1.01)
(13)	House value dummy (=1 if the house is worth more than 5000 yuan)			0.056	-0.037
				(0.08)	(0.07)
(14)	Number of Observations	1575	1575	1549	1549
(15)	R-squared	0.01	0.27	0.10	0.43

Highest R-square > 0.40

Table 3. DD Regression Results Analyzing the Effect of Migration on School Performance of Students in China by Household's Migration Status

	Treatment Variable (MIG_i)[b]	(1) Restricted & Unadjusted	(2) Unrestricted & Unadjusted	(3) Restricted & Adjusted[c]	(4) Unrestricted & Adjusted[c]
	Dependent Variable = Changes in Second Term Test Scores between 2002 and 2006 ($\Delta Score$)				
(1)	*Any_Parent_migrated,*	3.183	2.327	2.169	1.164
		(3.72)***	(3.03)***	(2.58)**	(1.65)*
(2)	*Father_Migrated_Only*	4.634	3.812	3.630	2.356
	(mother stayed home)	(4.27)***	(4.09)***	(3.45)***	(2.73)***
(3)	*Father_Migrated*	3.812	2.879	2.984	1.508
	(Unconditional)	(4.10)***	(3.52)***	(3.24)***	(1.98)**
(4)	*Mother_Migrated_Only*	0.839	0.156	-0.861	-0.121
	(father stayed home)	(0.45)	(0.08)	(0.45)	(0.07)
(5)	*Mother_Migrated,*	0.903	0.444	-0.147	-0.541
	(Unconditional)	(0.73)	(0.37)	(0.12)	(0.48)
(6)	*Both_parents_migrated*	1.367	0.615	1.040	-0.536
		(0.79)	(0.38)	(0.58)	(0.35)

Table 4. PSM and DDM Estimators and the Effect of Migration on the School Performance of Students in Rural China, 2002 and 2006

Treatment Variable [c d]		Propensity Score Matching: Average Treatment Effect for the Treated (1)	t-value/ z-value [b]	Difference-in-Difference Matching: Average Treatment Effect for the Treated (2)	t-value/ z-value [b]
Any_parent_migrated	(1a) Basic Matching	1.16	(1.02)	0.31	(0.28)
	(1b) Multi-dimensional Matching	1.57	(1.60)	2.12	(1.86)*
Father_Migrated_Only (mother stayed home)	(2a) Basic Matching	2.04	(1.36)	1.12	(0.77)
	(2b) Multi-dimensional Matching	3.59	(2.96) ***	3.12	(1.93)**
Father_migrated, (Unconditional)	(3a) Basic Matching	1.57	(1.20)	2.35	(1.93)**
	(3b) Multi-dimensional Matching	2.19	(2.04) ***	2.52	(1.99)***
Mother_Migrated_Only (father stayed home)	(4a) Basic Matching	-0.63	(-0.22)	-1.1	(-0.39)
	(4b) Multi-dimensional Matching	-0.94	(-0.43)	1.93	(0.58)
Mother_migrated (Unconditional)	(5a) Basic Matching	-0.45	(-0.26)	-1.51	(-0.88)
	(5b) Multi-dimensional Matching	-0.46	(-0.32)	0.82	(0.48)
Both_parents_migrated	(6a) Basic Matching	-0.22	(-0.09)	-0.56	(-0.23)
	(6b) Multi-dimensional Matching	-0.28	(-0.13)	0.97	(0.43)

Table 4. PSM and DDM Estimators and the Effect of Migration on the School Performance of Students in Rural China, 2002 and 2006

Treatment Variable [c d]		Propensity Score Matching: Average Treatment Effect for the Treated (1)	t-value/ z-value [b]	Difference-in-Difference Matching: Average Treatment Effect for the Treated (2)	t-value/ z-value [b]
Any_parent_migrated	(1a) Basic Matching	1.16	(1.02)	0.31	(0.28)
	(1b) Multi-dimensional Matching	1.57	(1.60)	2.12	(1.86)*
Father_Migrated_Only (mother stayed home)	(2a) Basic Matching	2.04	(1.36)	1.12	(0.77)
	(2b) Multi-dimensional Matching	3.59	(2.96) ***	3.12	(1.93)**
Father_migrated, (Unconditional)	(3a) Basic Matching	1.57	(1.20)	2.35	(1.93)**
	(3b) Multi-dimensional Matching	2.19	(2.04) ***	2.52	(1.99)***
Mother_Migrated_Only (father stayed home)	(4a) Basic Matching	-0.63	(-0.22)	-1.1	(-0.39)
	(4b) Multi-dimensional Matching	-0.94	(-0.43)	1.93	(0.58)
Mother_migrated (Unconditional)	(5a) Basic Matching	-0.45	(-0.26)	-1.51	(-0.88)
	(5b) Multi-dimensional Matching	-0.46	(-0.32)	0.82	(0.48)
Both_parents_migrated	(6a) Basic Matching	-0.22	(-0.09)	-0.56	(-0.23)
	(6b) Multi-dimensional Matching	-0.28	(-0.13)	0.97	(0.43)

Table 4. PSM and DDM Estimators and the Effect of Migration on the School Performance of Students in Rural China, 2002 and 2006

Treatment Variable (MIG_i)		Propensity Score Matching		Difference-in-Difference Matching	
		ATT	t-value/ z-value	ATT	t-value/ z-value
Any_parent_migrated	(1a) Basic Matching	1.16	(1.02)	0.31	(0.28)
	(1b) Multi-dimensional Matching	1.57	(1.60)	2.12	(1.86)*

Summary

- **There is no evidence that migration in our sample of households has hurt school performance.**
- **In fact, when the father outmigrates (either by himself or with others), migration appears to have a small, positive effect on the school performance of migrant children.**

Heterogeneous effects

- **Heterogeneous Effects from Wealth**

Model (5): $\Delta \mathbf{Score}i = \alpha + \delta_1 MIG_i + \delta_2 {*}MIG_i\ {*}poor + \gamma Score\_02_i + \beta X_i + \varepsilon_i$

- **Heterogeneous Effects from Household Composition**

Model (6): $\Delta \mathbf{Score}i = \alpha + \delta_1 MIG_i + \delta_2 {*}MIG_i\ {*}nosibling + \gamma Score\_02_i + \beta X_i + \varepsilon_i$

Table 5. DD Regression Results with Heterogeneous Effects from Wealth and Household Composition

Dependent Variable = Changes in Second Term Test Scores between 2002 and 2006 ($\Delta Score$)			
Panel A *Heterogeneity Effects from Wealth*[a]		Panel B *Heterogeneity Effects from Household composition*[b]	
Treatment Variable(MIG_i) [a]		Treatment Variable(MIG_i) [b]	
Any_Parent_Migrated	2.397	*Any_Parent_Migrated*	1.118
	(2.82)***		(1.28)
*Any_Parent_Migrated * Poor*	-2.271	*Any_Parent_Migrated * Nosibling*	0.195
	(1.79)*		(0.15)
Father_Migrated_Only (mother stayed home)	2.958	*Father_Migrated_Only (mother stayed home)*	2.028
	(2.83)***		(1.87)*
*Father_Migrated_Only*Poor*	-1.170	*Father_Migrated_Only*Nosibling*	0.965
	(0.72)		(0.57)
Father_Migrated (Unconditional)	2.668	*Father_Migrated (Unconditional)*	1.516
	(2.85)***		(1.60)
*Father_Migrated * Poor*	-2.139	*Father_Migrated * Nosibling*	0.028
	(1.54)		(0.02)
Mother_Migrated_Only (Father stayed home)	2.285	*Mother_Migrated_Only (Father stayed home)*	-0.828
	(1.59)		(0.40)
Mother_Migrated_Only Poor*	-3.783	*Mother_Migrated_Only* Nosibling*	1.680
	(1.28)		(0.48)
Mother_Migrated (Unconditional)	1.349	*Mother_Migrated (Unconditional)*	-0.403
	(0.99)		(0.29)
*Mother_Migrated * Poor*	-3.369	*Mother_Migrated * Nosibling*	-0.174
	(1.62)		(0.08)
Both_Parents_Migrated	1.720	*Both_Parents_Migrated*	0.155
	(0.87)		(0.08)
*Both_Parents_Migrated * Poor*	-3.982	*Both_Parents_Migrated* Nosibling*	-1.457
	(1.38)		(0.48)

Conclusion

- We can reject the hypothesis that migration harms the grades of their children .
- In fact, the migration of some migrant househol[d] has a statistically significant and positive effect [o] the performance of the children.
- There is neither a systematically different effect migration between the children of more wealthy and less wealthy households nor between the children from families that have one and more than one child.

Policy implications

- It is not that migrants do not need to have special attention in education … their grades are lower (but they are always lower) … increased education will raise their productivity (other studies) …
- Point of our paper: migration by itself does not cause this … although we have not identified that exact mechanism, may be that the income effect of migration is offsetting the parental care effect
- So should build better schools … have high quality boarding facilities … increase mentoring inside schools (e.g., by small classes) … and promote the admittance of rural students to urban schools (for low or no tuition) … but, don't do it because believe migration leads to lower education achievement … there is no evidence from our sample