Starting Early: Returns on Kindergarten Attendance in Indonesia

Daniel Posthumus

William & Mary - Economics

INTRODUCTION

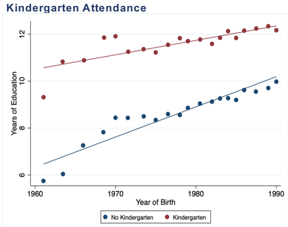
What effect does kindergarten attendance have on later-life educational outcomes in Indonesia?

- Extensive literature has shown the efficacy and motivation of early childhood programs. (Heckman, 2007; Duncan, et. al., 2022)
- Much of this work has focused on targeted programs in developed countries, like Head Start. (Garces, Thomas, and Currie, 2002)
- There is a lack of literature on universal preschool programs in developing countries, a gap that my work seeks to fill.

Indonesia is experiencing rapid economic growth and development, with increasing levels of educational attainment. As demonstrated in Figure 1, there's an association between kindergarten and more years of education.

Despite rising levels of access to and completion of schooling, there are concerns about the **quality** of schooling, and kindergarten is no exception – thus we want to understand the **causal effect** of kindergarten. (World Bank, 2020)

Figure 1: Years Of Education, By Year Of Birth And Kindergarten Attendance



METHODS

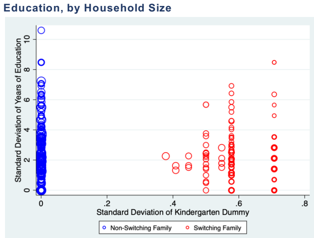
Like previous work about the long-term effects of early childhood programs, I use family fixed-effects; specifically, **mother fixed-effects.** (Garces, Thomas, and Currie, 2002) I am estimating the following equation:

$$Y_{if} = \beta_0 + \beta_1 \mathbf{KINDER}_{if} + \beta_2 \mathbf{X}_{if} + \mu_f + \epsilon_i$$

For individual i in family f, where KINDER is the kindergarten attendance dummy, $\mathbf{X}_{if}$ is a vector individual controls, Y is the educational outcome of interest, and μ is the mother fixed-effects.

This estimation method allows me to control for **all time-invariant characteristics of mothers,** observed as well as unobserved. I am thus only comparing between children of the same mother, for whom there is variation in kindergarten attendance – an approach that restricts my sample (see Figure 2 below) to "switching" families with such variation.

Figure 2: Within-Household Variation in Years of Education, by Household Size



DATA

My sample is taken from the Indonesian Family Life Survey (IFLS), a longitudinal household survey with 5 waves.

Using data from 1997 and 2014, I was able to create a longitudinal dataset, tracking individuals from their early childhood in 1997 to adulthood in 2014. The Survey also includes household- and community-level data I've incorporated into my regression analysis.

My sample consists of all children between the ages of 3 and 10 in 1997 who were individually interviewed in 1997 *as well as* 2014. Table 1 below shows summary statistics for my variables of interest:

Table 1: Summary Statistics for Variables of Interest

	Full Sample	Not Switching HH		Switching HH	
		No Kinder	Kinder	No Kinder	Kinder
Educational Variables					
Kindergarten	0.40	0.00	1.00	0.00	1.00
	(0.49)	(0.00)	(0.00)	(0.00)	(0.00)
Yrs of education (2014)	10.72	9.81	12.20	10.23	11.39
	(3.30)	(3.41)	(2.53)	(3.50)	(2.85)
Completed elementary	0.95	0.92	0.99	0.93	0.99
	(0.22)	(0.28)	(0.10)	(0.26)	(0.11)
Completed junior high	0.81	0.72	0.95	0.78	0.89
	(0.39)	(0.45)	(0.21)	(0.42)	(0.31)
Completed senior high	0.56	0.45	0.74	0.50	0.63
	(0.50)	(0.50)	(0.44)	(0.50)	(0.48)
Household Controls					
HH expenditure, per capita (ln)	12.14	12.01	12.37	12.05	12.22
	(0.69)	(0.64)	(0.71)	(0.64)	(0.73)
Electricity	0.86	0.79	0.95	0.84	0.89
	(0.35)	(0.41)	(0.21)	(0.37)	(0.31)
Mother's years of education	5.58	4.21	8.01	4.65	6.15
	(3.92)	(3.34)	(3.76)	(3.38)	(4.04)
# of mother's children	2.51	2.62	2.01	2.97	2.82
	(1.24)	(1.37)	(0.97)	(1.09)	(0.97)
Community Control					
Village's elementaries per person (ln)	-7.20	-7.12	-7.29	-7.19	-7.29
	(0.70)	(0.68)	(0.67)	(0.72)	(0.80)
Individual Controls					
Birth cohort	1.29	1.24	1.36	1.28	1.39
	(1.47)	(1.44)	(1.53)	(1.42)	(1.52)
Male	0.49	0.50	0.48	0.51	0.46
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Birth-order to mother	1.01	1.01	1.01	1.01	1.01
	(0.09)	(0.08)	(0.08)	(0.09)	(0.12)
Number of Observations	5439	2608	1603	679	549

RESULTS

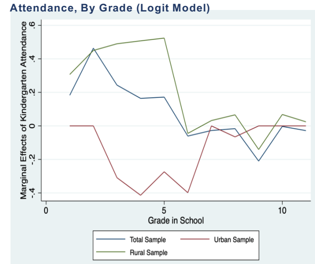
Table 2: Regression Analysis, Years of Education as the Outcome Variable

	(1)	(2)	(3)	(4)
Kinder	2.08***	0.99***	0.99***	0.16
	(0.16)	(0.14)	(0.14)	(0.18)
Urban		0.53*	0.58*	
		(0.31)	(0.31)	
Urban x Kinder		-0.30	-0.34	
		(0.26)	(0.26)	
Household Controls	NO	YES	YES	NO
Community Controls	NO	YES	YES	NO
Individual Controls	NO	NO	YES	YES
Mother Fixed-Effects	NO	NO	NO	YES
Adjusted R-squared	0.10	0.26	0.27	0.03
Number of observations	5439	5439	5439	5439

*** p<.01, ** p<.05, * p<.1. For lists of control variables, see header designations in Table 1.

My first set of regressions use years of education as the outcome variable; I find that the magnitude of kindergarten's goes from significantly positive in the basic OLS specifications to statistical insignificance with mother fixed-effects.

Figure 3: Kindergarten Marginal Effects On School Attendance, By Grade (Logit Model)



I also conduct a series of mother fixed-effects logit models, using school attendance in grade ***n*** as the outcome variable**.** There is some fadeout, as the positive marginal effects of attending kindergarten are present in the early grades of school, before quickly approaching to statistical insignificance.

Table 3: Regression Results, Binary Education Outcomes

	Fail elementary	Fail junior	Fail senior	Complete elementary	Complete junior	Complete senior
Attend kindergarten	-0.03	-0.00	0.01	0.03**	0.01	0.02
	(0.04)	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)
Male	0.06***	0.01	0.02**	-0.02**	-0.02	-0.02
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Birth order	-0.04	-0.00	0.00	-0.01	0.05	-0.00
	(0.09)	(0.00)	(0.00)	(0.03)	(0.04)	(0.04)
General health status (1997)	0.05**	0.00	-0.01**	-0.01	-0.00	-0.02
	(0.02)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)
Healthcare visits (1997)	0.01	-0.00	0.01*	0.01**	0.01	-0.02
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)
Adjusted R-squared	0.02	0.00	0.01	0.01	0.00	0.06
Number of observations	3415	3181	2712	5439	5439	5439

*** p<.01, ** p<.05, * p<.1

Next, I run a series of mother fixed-effects regressions, with a series of binary educational outcomes. My results for school completion dummies mirror those of my Logit models, with a statistically significant positive effect in early education fading out to insignificance as the student moves to junior and senior high school.

CONCLUSION

I find statistically significant positive effects of kindergarten attendance for primary school completion, although for medium- and long-term educational outcomes my finds are more mixed. These findings mirror the concept of "fadeout", that the effects of early childhood interventions fade out as a student ages.

Beyond primary school, my findings suggest that kindergarten programs aren't effective in improving longer-term educational outcomes when other factors, particularly mother characteristics, are controlled for.

FUTURE RESEARCH

My next step is to conduct an instrumental variable (IV) estimation of the effects of kindergarten attendance, with two instruments:

1. Kindergarten attendance rates by locality and age cohort
2. The presence of kindergartens in communities

I also plan on improving my fixed-effects models with time-varying mother characteristics, incorporating data from the 2000 and 2007 survey waves, as well as possibly the 1994 prenatal data on mothers.

There are also concerns about the validity of family fixed effects design, in particular selection bias into "switching status". It also appears that I have not yet controlled for the most significant explanators of within-household variation in educational outcomes, and I will work to find, and control for, those variables.

More broadly, the next step of this research is to examine the labor market outcomes associated with educational attainment, and specifically, kindergarten attendance in Indonesia.

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