Maternal migration and children development in Rural China

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Abstract

Early child development is important to human capital accumulation. Current studies find a positive effect of maternal migration on their early children development due to income increase and parenting knowledge improvement after migration. However, most of those studies didn't identify individual causal effect. This paper uses propensity score matching (PSM) and Bayesian Additive Regression Trees (BART) to identify individual and causal treatment effects of parental migration on early childhood development. Results of PSM suggest a statistically significant positive effect of maternal migration on children development outcomes and mental health levels who migrates with them. However, there is no statistically significant effect of maternal migration on left-behind child. By using BART, we found a negative effect of maternal migration on development outcomes for all of children. However, most children behave well on mental health level if mother migrate out. Findings show that one way to improve the development of children is to encourage women in rural areas to look for higher-paying jobs in cities.

Keywords: maternal migration; early child development; generalized propensity score, Bayesian Additive Regression Trees

1. Introduction

With accelerating process of urbanization in rural China, a large number of rural residents migrate to urban in seeking jobs, especially for females (Zhang, 2018; Cortes 2015). Female migrants contribute to local development, but also have larger influence on their child development because they are usually primary caregivers for children (Jia et al., 2016; Yue et al., 2020). Two phenomena are relevant to maternal migration. First, most children are being left by mothers and stay at registered locations, which refers to left-behind children (Duan and Zhou, 2005). Second, some children migrate to host cities with their mothers, we define them as migrant children (Mu and Jia, 2014). In China, there are 61 million left-behind children and 21 million migrant children under 18 years old in 2010, and among those two groups, around 5% of children are during their early children development stage (All China Women's Federation, 2013). Early child development refers to the period when children aged 0~3 years old which is thought to be a critical period affecting human capital accumulation through life (Gertler et al., 2014; Heckman & Mosso, 2014).

Current research shows mixed results about the effect of maternal migration on their early child development. One the one hand, there is a positive effect of increased income when mother migrates out (Antman, 2012; Ambler et al., 2015). Also, mothers could receive more information about parenting knowledge, which helps them improve parenting behaviors (McKee, Kelsey, et al., 2021). However, on the other hand, migration would harm the outcomes of children regardless of whether they stay with children or not. For left-behind children, they will suffer separation from their mother. Maternal separation has negative effect on children's hippocampus development, schooling outcomes, and social emotional (Baum et al., 2003). In addition, those children usually have poor parenting environment because grandmother will be prime caregivers after mother migrating out, but they luck scientific parenting knowledge (Wang and Mesman 2015; Yue et al., 2020). For migrant children, although they do not separate from their mother, they are under negative effect of discrimination both directly (e.g., inadequate health care) and indirectly (e.g., psychologically stressful) (Schmitt, Branscombe, Postmes, & Garcia, 2014). Whether maternal migration helps, or harms early child development depends on the balance of the (positive) effects of increased income and parenting information against the (negative) effects of parental absence (Antman 2012).

However, empirical estimation of the causal effect of parental migration on children development is complicated by the fact that decision of parental migration is endogenous to children development, which has not been solved by most of recent studies (Rachel et al., 2012; Zheng 2020; Chen et al., 2021). Also, most studies lack information about parental migration history, which will also lead to a biased result because the effect differs if children experience paternal migration at different points or duration in their lives (Zhang et al., 2011). In addition, there is importance of inferring individual-level treatment effects since for different household, parental migration period is distinct and treatment effects therefore are very often heterogeneous across units of analysis. In this paper, we conducted a survey to 781 households in a northwest province of China and include children aged 1-23 months (about 2 years) from those households.

We intend to identify the individual and casual treatment effect of maternal migration on early child development by using propensity score matching and Bayesian Additive Regression Trees (BART) method.

The remainder of this paper is organized as follows.: Section 2 describes the setting and data and discusses our empirical strategy. Section 3 presents the main results. Section 4 provides concluding comments and discusses the implications of our results as well as possible further research.

2. Method

2.1 Data collection

We collected data in two surveys rounds, referred to as the baseline and follow-up surveys. The baseline survey was conducted in two waves in October 2017 and April 2018 at the Maternal and Child Care Service Center in Shaanxi Province. 1,091 mothers with a gestational age of 20-32 weeks attended the survey. We record their telephone numbers and home address at the baseline survey. However, some of mothers changed home address or refused to attend follow-up survey, therefore we only followed 759 mothers in August 2019 and surveyed them at their household.

The primary outcome of interest in this study was child development outcomes. Specifically, the Caregiver Reported Early Childhood Development Instruments (CREDI, McCoy, Dana Charles, et al., 2018) and the social-emotional section of Ages & Stages Questionnaires (ASQ, Squires, Jane, Diane D., et al., 2009) were administered. The first scale included five domains: overall development, cognitive development, language development, motor development, and social-emotional development.

To collect maternal migration history, mothers were asked to recall their migration history from children born until survey date. Specifically, we collected dynamic information about whether mother go out and live with their children every month at their children's age.

To assess the impact of maternal migration on maternal knowledge, parenting behaviors and parenting investment, mothers have also been surveyed by several professional scales. Firstly, a parenting knowledge scale was used to evaluate maternal parenting knowledge during the baseline and follow-up surveys. The scale was developed by our research team and included four subsections: how to take care of mom themselves, knowledge about playing with child, knowledge about child sleep, knowledge about talking with child, and knowledge about child emotional development. We also surveyed mothers by Knowledge of Infant Development Inventory (KIDI) (David MacPhee, 1981). The accuracy of KIDI was calculated for samples by using the number of right answers divided by the total number of right and wrong answers. Secondly, a scale about positive parenting behaviors was also developed and administered, which evaluates mother's behaviors on how to interact with children. Thirdly, to assess the program effects on parental investments, a detailed questionnaire using the Family Care Indicators (FCI) developed by UNICEF (Frongillo, Sywulka, & Kariger, 2003) was given to the sample participants at the follow-up survey. Using mothers' responses to the FCI questionnaire, two measures of parental outcomes were created: material investments and time investments. Five variables were used to measure caregiver material investments: sources of play materials, varieties of play materials, number of picture books, number of books for adults, and number of magazines and newspapers in the home. Time investments were calculated based on whether mothers had participated in each of five at-home play activities with their child in the past three days: reading books or looking at picture books, telling stories, singing songs, playing with toys, and spending time in naming things, counting, or drawing.

Information on household and child characteristics were collected at the baseline and follow-up survey separately. Household information include parental age (years), education level, and whether the household attend Dibao program[1]. Basic child characteristics included their age (months), gender, whether they were a first-born child, and whether they are premature children.

2.2 Statistical analyses

Propensity-score matching (PSM)

Propensity-score matching was used to analyze the effect of maternal migration on child developmental outcomes, maternal parenting knowledge score, positive parenting behaviors, and parenting investment. Firstly, we use the monthly data to put kids into categories based on what age mothers and fathers were first gone. Then matching children with parents going out and leaving them at home to whom living at home with parents across those groups. Secondly, we make sever continuous variables for the fraction of time mother and father were gone and living with or separating from children and estimate a dose-response using a "generalized propensity score." Child developmental outcomes (CREDI) and FCI were standardized based on follow-up survey scores. ASQ was summarized into final scores across different groups. Parenting knowledge scores were standardized based on baseline scores. Positive parenting behaviors were summarized into an index by factor analysis. Control variables included child and household characteristics, which were collected in the baseline and follow-up surveys. Sample treatment status (randomly assigned) was also controlled as dummy variable[2].

Bayesian Additive Regression Trees (BART)

A sum-of-trees model and a regularization prior are the two parts of the BART algorithm. The prior prevents overfitting by specifying the number of trees, the probability distribution for the size of each tree, the shrinkage applied to the fit from each tree, and the degrees of freedom for the prior distribution for the residual standard error. Chipman et al. has more information about the model, the prior, and the fitting algorithms for those who are interested (2007, 2010).

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[1] China's minimum living standard guarantee program (Dibao) is a social assistant program in China, which aims to provide cash support to poverty household whose income is lower than certain level (Kakwani, N., Li, S., Wang, X., & Zhu, M. (2019). Evaluating the effectiveness of the rural minimum living standard guarantee (Dibao) program in China. China Economic Review, 53, 1-14.). In 2017, the critical level was $574 in Shaanxi province (http://www.mca.gov.cn/article/sj/tjjb/bzbz/2018/201803131535.html)

[2] This dataset from a filed experiment, which identify impact text massage program on children development outcomes. We didn't find significant results from this program, however, to control the potential impact, we controlled treatment status in the model.

The main point is that BART can be used to fit even highly nonlinear response surfaces in a flexible way. This is in line with our goal to fit E[Y (1) | X]-E[Y (0) | X] without making too many assumptions about the parameters.

It is easy to figure out the average treatment effect (ATE) with BART. First, fit BART to what was seen (Y given Z and X). Next, make forecasts for two sets of data (Hill 2011). X stays the same for both, but all treatment values are set to 0 in one and to 1 in the other. This lets BART draw from the posterior distribution for E[Y (1) | X] and E[Y (0) | X] for each person, which means we can also get draws from E[Y (1)Y (0) | X] for each person. In this study, the treatment is whether mother ever migrate out from baseline to follow-up survey, and outcomes Y is children development outcomes and mental health level.

3. Result

3.1 Maternal migration on early child development outcomes

In Appendix 1, we see the self-selection bias between migrant and non-migrant mothers. To overcome this threat, we use "generalized propensity score" to match the children based on maternal migration status. Results in Tables 1 present a positive and significant effect of maternal migration with children on their CREDI outcomes. Specifically, maternal migration with children leads to a 0.82 standard deviation increase in CREDI overall development, 1.0 standard deviation in language development, and 0.73 standard deviation in motor development. We find no significant effect on child cognitive and social emotional development when they migrate out with their mother. In addition, we find left-behind children have low development level at each domain compared to their peers when mother migrate out, which is also consistent with OLS results, but results are not significant after controlling selection bias.

Table 2 shows matching estimates of impact of maternal migration on intermediate outcomes. Panel A shows the effect on parenting material investment, panel B shows effect on parenting time investment, panel C shows effect on maternal parenting knowledge. We find that maternal migration without children has a clear negative effect on parenting material investment (Panel A, Table 4). Specifically, on average, children's source of play materials decreases 0.97 points, varieties of play materials decrease 1.2 points, play activities decrease 0.98 points. Also, household books increased about 10. In panel B of Table 4, we see that mother migrating without children leads to a reduction in their time engaged in stimulating activities with children. We find a 40% decrease in the number of mothers reporting that they sang songs to children the previous day. Other proportions of simulating activities are also decreased with the ration of maternal migrating time, although it is not significant. In panel C of Table 5, we find maternal parenting knowledge decreased significantly when they migrate out and separate with children, which is not consistent with previous studies. We find no significant result on intermediate outcomes when mother migrate out with children.

3.2 Maternal migration on early child development outcomes by using BART

Table 3 is a summary of the individual treatment effect using BART. Table 3 shows that, on average, when mothers migrate out, it hurts their children's overall development. In particular, when the mother moves away, the CREDI score of the children in the overall domine will go down by 0.17 standard deviation. The effect is smallest when it is -0.27, and it is smallest when it is -0.045. But maternal migration will benefit the mental health of most of children, although for few of students (3.9%), there is still negative effect. In particular, when the mother migrates out, the children's ASQ score goes down by -0.07 standard deviation. This means that the children's mental health is getting better, since a lower ASQ score means that the children's mental health is better. The least effect for ASQ is -0.40, and the most effect is 0.03. In the appendices 1 and 2, you can find the individual treatment effect on CREDI and ASQ, as well as the confidence interval for each household.

To explore how the individual treatment effect change with age, we sort the individual treatment effect by age and plot the effect and confidence interval in the Fig 1 and Fig 2. According to Fig 2, with the increase of age, effect of maternal migration on CREDI is decreasing, and the mean effect is around -0.25. The upper bound of effect is between 0.25 to 0.5 and low bound of effect is between -0.5 and -1. However, with the increase of age, effect od maternal migration on ASQ is increasing, and mean effect is around 0. The upper bound of effect is between 0 and 0.5, and lower bound is between -0.25 and -1.5.

4. Discussion

Previous research has found that maternal migration away from home has a negative effect on the early childhood development of left-behind children, especially for younger children; however, this effect becomes positive when children migrate with their mother. Despite these findings, estimation of the causal effects of parental migration on child development is complicated by the fact that the decision to migrate has an endogenous influence on child development. Moreover, most studies lack detailed information on maternal migration history, thus capturing only part of the story of parental migration’s effect on early childhood development.

By using propensity score matching, results of this study suggest a statistically significant positive effect of maternal migration on children development outcomes and mental health levels who migrates with them. However, there is no statistically significant effect of maternal migration on left-behind child. By using BART, we found a negative effect of maternal migration on development outcomes for all of children. But most children behave well on mental health level if mother migrate out, which is different from PSM results, but its more accurate since it displays an individual treatment effect. We also find that positive effect of maternal migration will increase with children’age. Findings show that one way to improve the development of children is to encourage women in rural areas to look for higher-paying jobs in cities.

Table 1. Effect of maternal migration on children development

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CREDI standardized score for the overall development	CREDI standardized score for the cognitive domain	CREDI standardized score for the language domain	CREDI standardized score for the motor domain	CREDI standardized score for the soc-emot. domain	ASQ raw score at follow-up survery	ASQ final score at follow-up survery	ASQ is at risk (1=yes)
Migration & no separation ratio	0.821*	0.628	1.005*	0.731*	0.582	-22.145	-22.697	-0.044
	(0.442)	(0.440)	(0.540)	(0.423)	(0.417)	(16.405)	(16.360)	(0.163)
Migration & separation ratio	-0.766	-0.768	-1.010	-0.703	-0.398	23.696	23.349	0.102
	(0.641)	(0.637)	(0.784)	(0.613)	(0.604)	(21.874)	(21.826)	(0.231)
Observations	683	683	683	683	683	680	680	692

Standard errors in parentheses
* p<0.10; ** p<0.05; * p<0.01

Table 2. Effect of maternal migration on parenting investment and knowledge

	Panel A Material Investment			
	(1)	(2)	(3)	(4)
	Sources of play materials	Varieties of play materials	Play activities	Household books
Migration & no separation ratio	0.546	0.837	0.381	-1.354
	(0.346)	(0.553)	(0.528)	(2.456)
Migration & separation ratio	-0.966***	-1.211**	-0.982*	-10.475***
	(0.371)	(0.597)	(0.566)	(2.633)
Observations	761	760	760	759
	Panel B Time Investment			
	(6)	(7)	(8)	(9)
	Telling story books with children yesterday	Singing with children yesterday	Playing outside with children yesterday	Playing toys with children yesterday
Migration & no separation ratio	-0.085	0.147	0.052	0.070
	(0.170)	(0.169)	(0.144)	(0.143)
Migration & separation ratio	-0.061	-0.427**	-0.179	-0.160
	(0.183)	(0.181)	(0.155)	(0.153)
Observations	760	760	760	760
	Panel C Parenting Knowledge			
	(10)	(11)	(12)	
	Standardized values of (end_kidi_Total)	KIDI accuracy score	Standardized values of (end_knowledge)	
Migration & no separation ratio	0.377	0.031	0.503	
	(0.353)	(0.034)	(0.310)	
Migration & separation ratio	-0.413	-0.096***	-1.107***	
	(0.377)	(0.037)	(0.326)	
Observations	766	766	773	

Standard errors in parentheses
* p<0.10; ** p<0.05; * p<0.01

Table 3. Maternal Migration Effect

	Min	1st Qu	Median	Mean	3rd Qi	Max	Num of >0
CREDI	-0.27448	-0.19196	-0.16599	-0.16563	-0.13965	-0.04531	0
ASQ	-0.40315	-0.06456	-0.04074	-0.07059	-0.02192	0.02929	28 (3.9%)

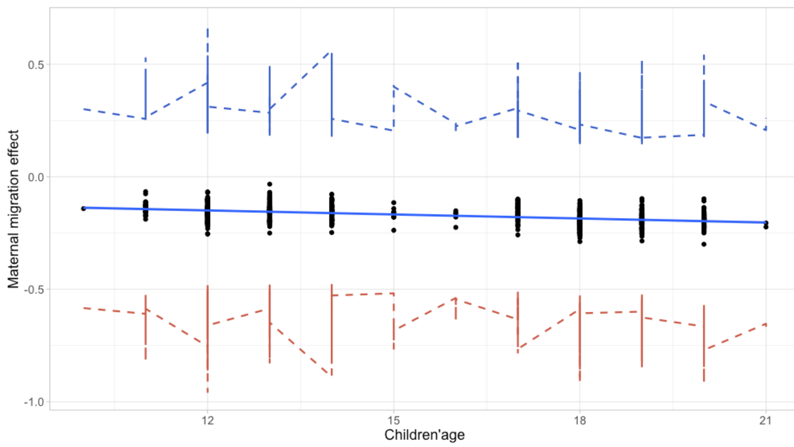

Fig 1. Effect of maternal migration on children CREDI score

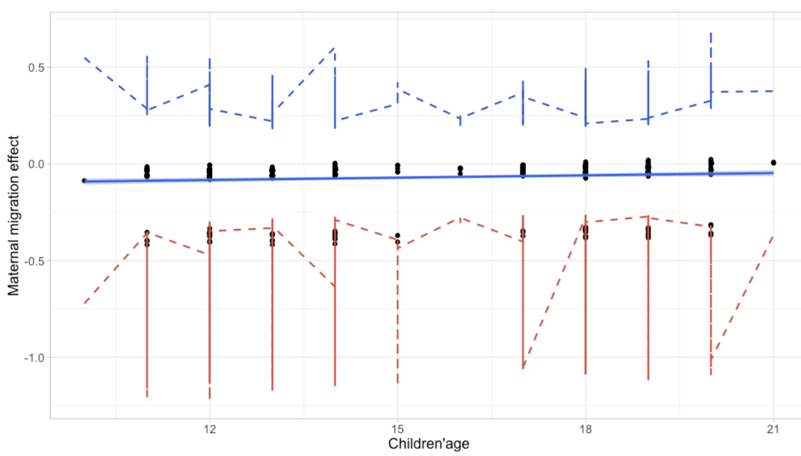

Fig 2. Effect of maternal migration on children ASQ score

Appendix 1. Comparisons of the sample characteristics between the migrant and non-migrant household

	Full sample	Non-migrant	Migrant	(1) vs. (2) p-value
	(1)	(2)	(3)	(4)
Age of child (months)	15.585	15.450	15.952	0.054
	(3.103)	(0.131)	(0.222)	
Female (1=yes;0=no)	0.557	0.561	0.560	0.967
	(0.497)	(0.021)	(0.036)	
Whether child is first baby in the family (1 = yes; 0 = no)	0.412	0.340	0.617	0.000
	(0.493)	(0.020)	(0.035)	
Premature birth (1 = yes; 0 = no)	0.055	0.050	0.071	0.310
	(0.228)	(0.010)	(0.021)	
Paternal age (year)	29.160	29.527	27.675	0.000
	(4.559)	(0.196)	(0.253)	
Maternal age (year)	26.665	26.970	25.244	0.000
	(4.308)	(0.184)	(0.257)	
Parental education[1]	3.528	3.448	3.645	0.010
	(0.939)	(0.039)	(0.066)	
Maternal education[1]	3.390	3.297	3.553	0.000
	(0.922)	(0.036)	(0.063)	
Household receives government welfare (1 = yes; 0 = no)	0.099	0.105	0.102	0.894
	(0.299)	(0.013)	(0.022)	
Treatment group (1=yes; 0=no)	0.501	0.483	0.523	0.330
	(0.500)	(0.021)	(0.036)	
CREDI standardized score for the overall development	0.324	0.339	0.266	0.499
	(1.285)	(0.054)	(0.096)	
CREDI standardized score for the cognitive domain	0.258	0.270	0.199	0.513
	(1.281)	(0.054)	(0.096)	
CREDI standardized score for the language domain	0.429	0.455	0.338	0.375
	(1.566)	(0.065)	(0.119)	
CREDI standardized score for the motor domain	0.224	0.236	0.178	0.583
	(1.241)	(0.052)	(0.091)	
CREDI standardized score for the soc-emot. domain	0.415	0.428	0.365	0.545
	(1.215)	(0.051)	(0.090)	
ASQ raw score at follow-up survery	71.449	69.497	77.094	0.055
	(46.072)	(1.914)	(3.646)	
ASQ final score at follow-up survery	22.465	20.560	27.956	0.061

	(45.967)	(1.909)	(3.639)	
ASQ is at risk	0.742	0.613	0.716	0.009
	(0.438)	(0.020)	(0.032)	
N	770	573	197	

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