The Effect of Maternal Migration on Early Childhood Development in Rural China

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Abstract

Nearly a quarter of all children under the age of two in China are left behind in the countryside as parents migrate to urban areas for work. We use a longitudinal survey following young children and their caregivers from 6 to 30 months of age to estimate the effects of maternal migration on development, health, and nutritional outcomes in the critical first stages of life.We find significant negative effects on cognitive development and indicators of dietary quality. Taken together with research showing long-term consequences of early life insults, our results imply that, although the reallocation of labor from rural to urban areas has been a key driver of China's prosperity in recent decades, it may entail a significant human capital cost for the next generation.

JEL Classification: J13, I21, I15, J61, O12

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1 Introduction

The largest movement of people in modern history has occurred in China as rural residents migrate to urban areas in search of off-farm work (Chan, 2013). For multiple social and institutional reasons, it is common for parents migrating to the city to leave their children in the care of family members in their home communities (All China Women's Federation, 2013). According to 2010 national census data, there are approximately 61 million so-called "left-behind" children under 17 years old in China's countryside (UNICEF et al., 2014).

In this paper, we study the effects of maternal migration on development outcomes in early childhood. Approximately 11.7 million left-behind children are under the age of two – accounting for more than a quarter of all 0-2 year olds in China (UNICEF et al., 2014). Parental migration during this period could be particularly consequential given that early childhood is thought to be a critical period for human capital accumulation. Over the last few decades, work across multiple disciplines has highlighted the importance of the earliest stages of life for wellbeing throughout the life cycle (Currie and Almond, 2011). Research in neurobiology, psychology, and economics all point to the significance of environments in the early years of life for the acquisition of human capital (Knudsen et al., 2006). Research on child nutrition in particular emphasizes the key role played by the 'critical first 1000 days', including the prenatal period and first two years after birth, with some studies suggesting that nutritional insults in this period are difficult to reverse at later ages (Martorell et al., 1994; Victora et al., 2008; Hoddinott et al., 2008; Maluccio et al., 2009). Long-term follow-ups of interventions have shown that investments in the cognitive development, nutrition, and health of young children have consequences for later life outcomes including ultimate educational attainment, earnings, adult health, and even participation in crime (Victora et al., 2008; Campbell et al., 2014; Hoddinott et al., 2008; Maluccio et al., 2009; Schweinhart et al., 2005; Heckman, 2006).

We use a unique panel dataset of young children and their caregivers to estimate the causal effects of maternal outmigration on development, health, and nutrition indicators in the critical first few months of life. We use variation generated by a rapid outmigration of mothers in the first two years after childbirth in combination with outcomes measured at six-month intervals for two years to estimate the impacts of maternal migration. We address endogeneity by controlling for child fixed-effects over the four survey rounds conducted from when children were 6-12 months of age to 24-30 months of age. We evidence the credibility of this identification strategy with robustness checks of its primary underlying assumptions.

A priori, the effect of parental migration on early childhood outcomes is not clear. Whether parental migration helps or harms the outcomes of children left behind depends on the balance of the (likely positive) effects of increased income against the (likely negative) effects of parental absence (Antman, 2013). Although parental migration will presumably lead to an increase in household income and resources available to invest in children, parental absence could adversely affect children depending on how the time, attention, and decision-making of remaining caregivers substitutes for that of the migrating parent. The net effect of parental migration, therefore, depends on how any resulting increase in investments affects child outcomes and the degree to which these effects are counteracted by the effects of the absence of migrating parents.

Relative to older children, there are reasons to believe that the influence of parental absence is more likely to outweigh income effects for the very young. Meeting the material needs of young children is relatively inexpensive (at least in the Chinese context) compared to older children. Even in poor areas of China, the cost of providing goods necessary for a healthy and stimulating environment are well within the means of most households, particularly given low fertility rates. At the same time, parental absence during early childhood may have large negative and long-term effects. Studies from different disciplines suggest that maternal absence, specifically, during early childhood can be detrimental to development outcomes. Research in neuroscience has shown that maternal support in early childhood (but not later in childhood) is strongly associated with the development of the hippocampus – the region of the brain thought to be integral to memory, learning and emotion – into adolescence (Luby et al., 2012, 2016).[1] Social science research in developed countries has also shown early childhood to be a sensitive period for the effect of maternal-child separation. These studies have shown maternal-child separation due to employment during the first year of a child's life has negative effects on developmental and later schooling outcomes, but maternal employment has more mixed effects thereafter (Ermisch and Francesconi, 2013; Baum II, 2003; Han et al., 2001; Waldfogel et al.,

[1]This finding for human children echoes numerous studies using rodents showing that early maternal care has a large effect on hippocampal development in rat pups and that this operates through an epigenetic mechanism (Liu et al., 1997; Meaney, 2001; Fish et al., 2004; Szyf et al., 2005).

2002; James-Burdumy, 2005).

In addition to the likely importance of maternal support during early childhood, we focus our analysis on maternal migration for two other reasons. First, in China and internationally, the share of migrants who are women is increasing as is the fraction of migrant women who have children when they migrate (Cortes, 2015; De Brauw et al., 2008; Connelly et al., 2012; Mu and de Brauw, 2015). Second, maternal migration is likely to accompany significant changes in caregiving practices and investments. Given that the mother is often the second parent to migrate, primary caregiving typically falls to other remaining family members and likely represents a large shift in parenting practice as a result (in China, this is typically paternal grandmothers – Wang and Mesman (2015)). Caregivers who remain may have different preferences from parents that affect how the household budget is allocated and what material investments are made in children.[2] They may invest less time engaging in stimulating activities with children and be less knowledgeable of or less attentive to the nutritional and health needs of children (Tan et al., 2010). Maternal migration is thus both increasingly common and likely represents a large shift in caregiving practices that could have large effects on the cognitive, physical and emotional development of young children.

We find that maternal outmigration has significant negative effects on cognitive development for young children in rural China. Without regard to the exact timing that mothers leave, we estimate that maternal migration between six months and two years of age reduces the cognitive scores of infants and toddlers by 0.15 standard deviations (sd). These effects are mirrored by decreases in caregiver time engaged in stimulating activities. Maternal migration also has significant negative effects on indicators of dietary quality and weaker evidence that these extend to effects on linear growth and weight. We do not find significant effects of maternal migration on psychomotor development, socio-emotional delay, anemia, or the frequency of illness.

We also find that the timing of maternal outmigration matters. Earlier migration (when children are less than 15 months) is particularly consequential and has large sustained effects on cognitive development. We estimate that early maternal migra-

[2]Divergent preferences, particularly with the older generation, may include increased preference toward male children. Meyerhoefer and Chen (2010)find that parental labor migration in China is associated with a significant lag in the educational progress of girls and argue that this is due to shifting girls' time allocation toward home production. Chang, Dong, and MacPhail (2011) also show that migration in China increases work time for girls and not boys.

tion reduces cognitive scores measured at 24-30 months of age by 0.31 standard deviations. For comparison, recent intensive parenting interventions in Colombia and China increased comparable measures of cognitive development by around 0.25 sd (Attanasio et al., 2014; Sylvia et al., 2016).

Our findings contribute to the literature on the effects of parental migration on left-behind children in China and elsewhere.[3] In China, this literature has focused on children of school-age, showing mixed effects on schooling and health outcomes. Notable exceptions to this focus on school-aged children are de Brauw and Mu (2011) and Mu and de Brauw (2015) who study the effects of parental migration on the nutritional status of young left-behind children 2 to 7 years of age. After addressing the endogeneity of parental migration decisions, they find no effect on height but that weight-for-age increases by 0.19 sd. Using data from the same survey, Li, Liu and Zang (2015) also find that parental migration increases the probability of illness for 0 to 6 year olds.

Outside of China, we are aware of one study of the causal effect of parental migration in early childhood development. Macours and Vakis (2010) estimate the effect of seasonal migration on ECD outcomes in rural Nicaragua. They find that shock-driven migration of mothers has a positive effect on cognitive development for children 3 to 7 years of age and attribute this to changes in income and intra-household empowerment that come with maternal migration offsetting lack of parenting.

Our study adds to the literature on the effects of parental migration on left-behind children in China and elsewhere in three main ways. First, to our knowledge, this is the first study in or outside of China to estimate the effects of parental migration on cognitive, psychomotor, and socioemotional development during the critical first two years of life. Second, our dataset includes an unusually rich set of early childhood development, nutritional, and health outcomes allowing us to estimate effects across multiple domains. Finally, multiple rounds of data collection conducted in short

[3]Well-identified studies in this literature include de Brauw and Giles (2008) and Hu (2012) who find a negative relationship between internal migration opportunities and high school enrollment; Chen et al. (2009) who find a positive effect of paternal outmigration on educational performance among primary school students; Meyerhoefer and Chen (2010) who find that parental labor migration in China is associated with a significant lag in the educational progress of girls; Zhang et al. (2014) who conversely find that migration of both parents reduces test scores for primary school students but the migration of one parent has no significant effect; Xu and Yu (2015) find no effect of parental migration on a variety of outcomes for left-behind children; and Li, Liu and Zang (2015) who find that left-behind children are more likely to get sick or develop chronic health conditions relative to children living with their parents. See Wang and Mesman (2015) for a review of the English and Chinese literature.

intervals covering children from 6 to 30 months of age allows us to estimate the effects of migration during different stages of early childhood development.

The rest of this paper is organized as follows. In the next section, we describe the data and discuss our strategy for identifying the effects of maternal outmigration on child development and health outcomes. We present our results in Section 3 and conclude in Section 4.

2 Data, Variables, and Empirical Strategy

2.1 Sampling and Data Collection

The data used in this study come from a survey of children and households conducted by the authors in 11 nationally-designated poverty counties[4] located in southern Shaanxi Province. Shaanxi is a relatively poor province located in Western China, ranking 19 out of 31 provinces nationally in terms of GDP per capita with a per capita income of 6,503 yuan ($1,032) in 2013 (National Bureau of Statistics 2014). In terms of rates of migration, this region is comparable to other rural areas in northwest China. According to the National Bureau of Statistics, Shaanxi ranks 13$^{\text{th}}$ out of China's 31 provinces in terms of the percentage of rural children between the ages of 0 and 17 that are left behind (33% - Duan et al. (2013).

To choose households, we followed a multistage cluster sampling design. From each of the 11 counties, we included all townships not housing the county seat (townships are the middle level of administration between county and village) in the sampling frame.[5] In each of the 174 townships included, we then randomly selected two villages. In these villages, we obtained a list of all registered births over the past 12 months. We then enrolled children and their caregivers in the survey in two waves, once in April of 2013 and again in November of 2013. Each time, we enrolled all children between 6 and 12 months of age. Our baseline sample consists of 1,834 children and their caregivers.

Following an initial baseline survey wave in April/November 2013, we conducted three follow-up surveys at six month intervals until April 2015. Thus, survey waves

[4]As of 2012, there are 592 nationally designated poverty counties in China. Poverty counties are designated for the purposes of targeting under the poverty alleviation program.

[5]We excluded the one township in each county that housed the county seat since its level of development was often much higher than the non-county seat rural towns in the county.

were conducted when children were 6-12 months old, 12-18 months old, 18-24 months old and 24-30 months old.[6] In each wave of the survey, surveys of trained enumerators collected detailed information on characteristics of the child and household, indicators of child development and health and nutrition status, as well as extensive information on parenting and feeding practices.

2.2 ECD, Nutrition, and Health Outcomes

A key strength of this dataset for the purposes of this paper is the extensive information collected on various dimensions of child development, nutrition and health. In each survey round, we collected information on cognitive, psychomotor, and socio-emotional development; anthropometric measurements; and child illnesses. In each survey round, we also asked about intermediate outcomes related to the child rearing/parenting environment and feeding practices.

Cognitive and psychomotor development was assessed using the Bayleys scales of infant development (BSID-I). The BSID is considered the gold standard for assessing infant and toddler development and is used extensively in the psychological and health literature (Rubio-Codina et al., 2016). The BSID-I was formally adapted to the Chinese language and environment and scaled according to an urban Chinese sample (Yi et al., 1993). The BSID was administered by trained testers who underwent a formal week-long course including 2.5 days of field training. The test yields two indices: a mental development index (MDI) which evaluates memory, habitation, problem solving, early number concepts, generalization, classification, vocalizations, and language to produce a measure of cognitive development; and a psychomotor development index (PDI) which assess fine and gross motor skills to produce a measure of psychomotor development. Both indices are scaled relative to the distribution of scores in a reference population of "healthy/normal" children in China. Children are considered delayed with index values below 80.

As a measure of socioemotional development, we use the Ages and Stages Socio-Emotional Questionnaire (ASQ:SE). The ASQ:SE is an instrument administered to caregivers to screen for socio-emotional delay. It consists of a series of age-appropriate questions about child behavior and caregiver-child interactions. Based on caregiver responses to these questions, the ASQ:SE indicates children at risk of

[6] To ease interpretation of the results, we exclude the final wave (April 2015) for the first cohort of children when they were 30-36 months of age. Results are similar if these data are included.

socio-emotional delay. In the analysis, we generate an indicator which is 1 if a child is deemed at risk in a given survey wave and zero if not.

In addition to these development indicators, we also collected anthropometric information on each child as indicators of nutrition and health status. To assess anemia status, nurses from Xi'an Jiaotong Medical School collected hemoglobin concentrations from all children using a HemoCue Hb 201+ finger prick systems (Hemocue, Inc, Ängelholm, Sweden). For children in our age range, the WHO considers them anemic if their hemoglobin concentration is less than 110 g/L (World Health Organization, 2011).

Nurses embedded in survey teams also recorded the length/height and weight of children in each survey round. Using these measurements, we construct three standardized indicators using WHO growth charts (World Health Organization, 2009): length/height-for-age (HAZ), weight-for-age (WAZ), and weight-for-height (WHZ) z-scores. HAZ scores measure cumulative nutritional investments and illnesses over time and are known to be particularly sensitive to insults when children are under two years of age (World Health Organization, 1983; Schroeder et al., 1995). Reduced HAZ scores have also been linked to micronutrient deficiencies in Zinc, Vitamin A, and Iron (Rivera et al., 2003). WAZ and WHZ scores, in contrast, are thought to be more sensitive to immediate changes in diet. Note that these measures may move in opposite directions. It is possible for high energy diets, for example, to contribute to weight gain and reduced linear growth depending on dietary content (Shariff et al., 2016).

As indicators of general health, we use caregiver responses to questions about episodes of illness in the past month. In each survey round caregivers were asked if children had been ill with diarrhea, fever, cold, cough and indigestion in the past month.

In addition to the above ECD, nutrition, and health indicators, we also estimate the impacts of maternal migration on intermediate outcomes related to the child rearing/parenting environment and feeding practices. In regards to the child rearing environment, we asked caregivers about time spent with their children in specific activities in the past 24 hours, including: playing, telling stories, reading, and singing, as well as engaging in other stimulating activities. For intermediate outcomes related to nutrition, we construct measures based on breastfeeding, formula feeding, the feeding of solid foods, and – given the high burden of iron deficiency in the area –

feeding of iron supplements. For each wave, we construct measures based on the Indicators of Infant and Young Child Feeding (IYCF) developed by the WHO (World Health Organization, 2010). These indices are specifically designed to account for dietary transition to solid foods that typically begins around six months of age in China.

2.3 Maternal Migration in Early Childhood

As with similar studies, a key issue is how migration is defined. In each survey round we asked whether the child's mother was at home and if not when she left. We are therefore able to determine when migrating mothers left during the time between each survey wave. Using this information, we consider a mother to have migrated if, at the time of each survey round, she had been gone for more than three months (i.e. more than half of the time) since the previous survey round. Note that this definition does not distinguish maternal absence for work from absence for other reasons, however only a small fraction (2.1%) of mothers were absent for non-work reasons.

Figure 1 illustrates the pattern of maternal migration that we observe in our sample. For each of the four survey waves, when children were 6-12 months, 12-18 months, 18-24 months, and 24-30 months, we plot the fraction of children whose primary caregiver was the child's mother, the child's grandmother, or someone else. Over this short time period, the fraction of children whose primary caregiver is the mother falls by 27% (from 82% to 60%). Mothers of 40% of the children in our sample were absent by the time children reached 24-30 months of age.

To simplify the interpretation of our analysis, we exclude from the main analysis below sample households where the mother returned or left and returned during the study period (245 households, 13.4% of the sample). In the final dataset, therefore, all migration that occurs is outmigration.

2.4 Descriptive Analysis of Maternal Migration and ECD Outcomes

We present descriptive statistics to characterize the phenomenon of maternal migration in early childhood in China. First, we explore observable differences between households in which mothers did not emigrate at any point during the survey and those where the mother did. Table 1 compares characteristics of infants and house-

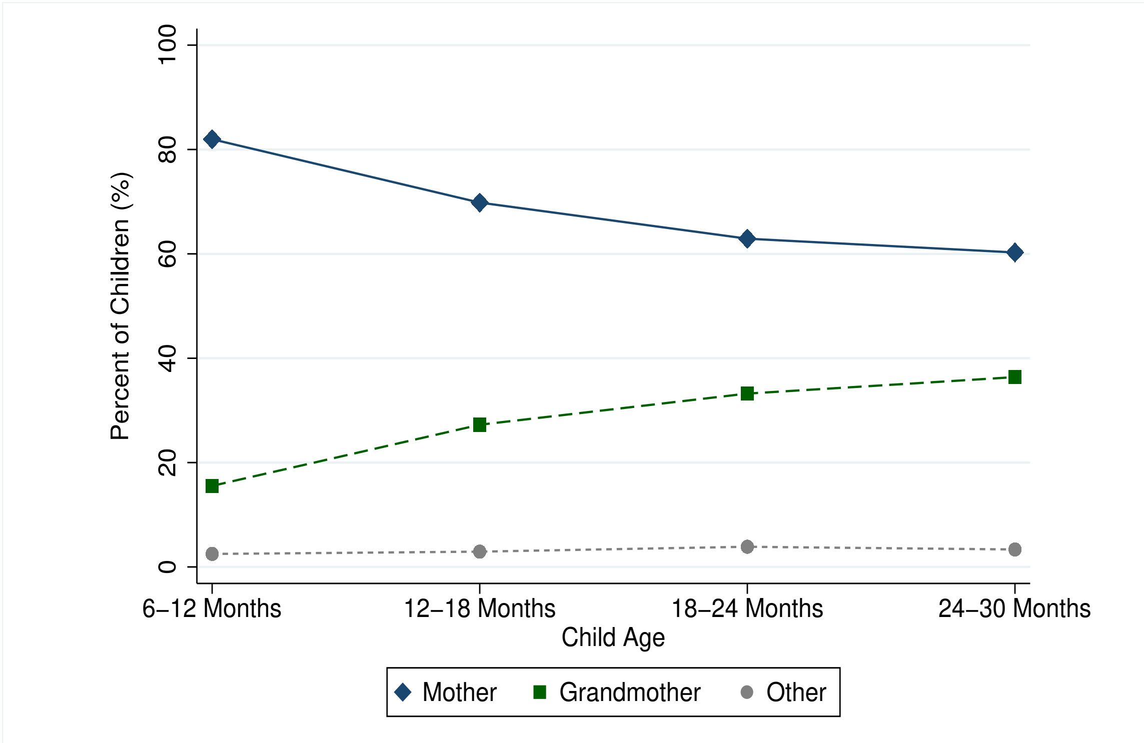

Figure 1: Primary Caregiver by Child Age.
Source: Authors' data.

holds in the two types of households at baseline (when children were 6-12 months old).

Three results here are particularly informative of the context. First, at baseline a large fraction of children in our sample are delayed and malnourished. 14% of 6-12 month olds are cognitively delayed (with Bayleys MDI<80) while 24% are delayed in their psychomotor development (PDI<80) (Rows 2 & 4). According to the ASQ:SE instrument, almost 40% of infants are at risk of socioemotional delay (Row 5). Finally, more than half of infants are anemic (Row 7). If these results are indicative of other rural areas, they imply that a large number of children in rural China are at risk of not reaching their potential. This is true for children in both migrant and non-migrant households.

Second, we find evidence of positive selection of mothers into migration in terms of child outcomes. Infants whose mothers later migrated have higher Bayleys MDI scores (Row 1), have higher hemoglobin concentrations (Row 6), and have higher HAZ and WAZ scores (Rows 8 and 9) than children of mothers who never migrate.

Table 1. Summary Statistics

	Full Sample	Non-migrant Mother	Migrant Mother	Difference: (2)-(3)
	Mean (Std. Dev.) (1)	Mean (Std. Dev.) (2)	Mean (Std. Dev.) (3)	*P*-value (4)
Panel A: Development outcomes				
(1) Bayleys mental development index (MDI)	96.673	96.295	98.042	0.093
	(16.891)	(16.959)	(16.597)	
(2) Cognitively delayed (Bayley MDI below 80)	0.139	0.148	0.110	0.077
	(0.346)	(0.355)	(0.313)	
(3) Bayleys psychomotor development index (PDI)	89.981	89.923	90.190	0.803
	(17.365)	(17.494)	(16.914)	
(4) Psychomotor development (Bayley PDI below 80)	0.240	0.242	0.231	0.694
	(0.427)	(0.428)	(0.422)	
(5) Socioemotional delay (1=yes; 0=no)	0.392	0.384	0.421	0.213
	(0.488)	(0.487)	(0.495)	
Panel B: Health outcomes				
(6) Hemoglobin concentration (g/L)	108.761	108.479	109.779	0.096
	(12.669)	(12.878)	(11.849)	
(7) Anemic (Hb below 110 g/L)	0.505	0.513	0.478	0.254
	(0.500)	(0.500)	(0.500)	
(8) Weight for age z-score	0.349	0.323	0.446	0.045
	(0.994)	(1.016)	(0.905)	
(9) Height for age z-score	0.103	0.075	0.205	0.074
	(1.180)	(1.182)	(1.169)	
(10) Weight for height z-score	0.361	0.346	0.415	0.326
	(1.144)	(1.166)	(1.062)	
(11) Times ill in past month	1.078	1.084	1.060	0.691
	(0.025)	(0.029)	(0.050)	
Panel C: Child Characteristics				
(12) Age of child (months)	8.912	8.856	9.113	0.025
	(1.855)	(1.863)	(1.816)	
(13) Female	0.469	0.471	0.463	0.785
	(0.499)	(0.499)	(0.499)	
(14) Premature birth	0.111	0.116	0.095	0.296
	(0.320)	(0.327)	(0.294)	
(15) Has siblings	0.224	0.263	0.083	0.000
	0.417	(0.441)	(0.276)	
Panel D: Household Characteristics				
(16) Age of mother above 25	0.520	0.564	0.359	0.000
	(0.500)	(0.496)	(0.480)	
(17) Mother completed junior high	0.171	0.157	0.223	0.005
	(0.377)	(0.364)	(0.417)	
(18) Father completed junior high	0.058	0.045	0.104	0.000
	(0.233)	(0.208)	(0.306)	
(19) Father at home	0.460	0.499	0.318	0.000
	(0.499)	(0.500)	(0.466)	
(20) Grandmother healthy	0.409	0.379	0.519	0.000
	(0.492)	(0.485)	(0.500)	
(21) Grandmother completed primary school	0.160	0.120	0.303	0.000
	(0.367)	(0.326)	(0.460)	
(22) Asset index	-0.011	-0.044	0.108	0.038
	(1.191)	(1.175)	(1.240)	
(23) Household receives social security support under	0.242	0.260	0.178	0.002
Dibao	(0.429)	(0.439)	(0.383)	

Notes: Descriptive statistics of child and houshold characteristics when children 6-12 months of age. Data source is author's survey. The first column shows the mean and standard deviation of each characteristic for the full sample; column 2 shows statistics for children and households where the mother does not migrate during the study period; column 3 shows statistics for children and households where the mother migrates at some point before children are 30-36 months of age. Socioemotional delay determined using the Ages and Stages: Socio-Emotional (ASQ:SE) questionnaire. Father at home is 1 if the father has been at home for a majority of the past six months at the time of the baseline survey and zero otherwise. Whether grandmother is healthy based on self-reported general health. Asset index constructed using polychoric principal components on the following variables: tape water, toilet, water heater, wash machine, computer, internet, fridge, air condition, motor or electronic bicycle, and car.

This positive selection is consistent with what has been found for older left behind children (Zhou et al., 2015). There is also evidence of positive selection in terms of parent and household characteristics: parents in migrant households are more educated and more wealthy (they have more household assets and are less likely to receive social security support under the *dibao* program).

Finally, this table gives an indication of main drivers of maternal migration during early childhood. First, migrants are much less likely to have a child older than the sample child. Only 8% of migrant households have an older child while 26% of households where the mother does not later migrate do (Row 15). Second, mothers are more likely to migrate if husbands are already out working at baseline (Row 19). Third, paternal grandmothers of left-behind children tend to be healthier and more educated (Rows 20 & 21). This likely reflects the fact that in absence of parents, grandparents are the default primary caregivers. If grandparents are more capable, parents may believe the costs of migration in terms of negative effects on their children are lower.

We further analyze the correlates of maternal outmigration in Table 2. The first three columns of this table show coefficients from a linear probability model where the dependent variable is one if mothers migrate at any time before children are 24-30 months. The conditional correlations in these regressions are largely consistent with the differences in means across migrant and non-migrant households discussed above. These regressions show that mothers who already have a child are approximately 9 percentage points less likely to migrate once other household characteristics are controlled for (Columns 2 and 3, Row 4). Migrant mothers are also likely to be younger (Row 8). They are more likely to migrate if their husbands are more educated or have already migrated at baseline (Rows 10 & 11). They are also more likely to migrate if paternal grandmothers are healthier or have a higher level of education (Rows 12 and 13). Finally, they are less likely to migrate if they receive social security support under *dibao*, China's rural minimum living standard guarantee program (Row 15).

The second set of columns shows – conditional on migration – marginal effects from an ordered probit regression where the dependent variable is the wave in which mothers migrated. This variable is coded so that higher values correspond to migrating later (i.e. it is 1 if they migrate in the first survey round, 2 if they migrate in the second survey round and so on). These regressions suggest that more

Table 2. Correlates of Maternal Migration

Dependent variable:	Ever Migrated			Timing of Migration		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Child Characteristics						
(1) Age of child (months)	0.014**	0.013**	0.014**	-0.082**	-0.081**	-0.085**
	(0.006)	(0.006)	(0.006)	(0.035)	(0.036)	(0.037)
(2) Female	-0.002	-0.011	-0.011	-0.033	0.007	0.016
	(0.021)	(0.020)	(0.019)	(0.113)	(0.111)	(0.111)
(3) Premature birth	-0.034	-0.027	-0.027	0.137	0.132	0.121
	(0.029)	(0.028)	(0.028)	(0.186)	(0.193)	(0.187)
(4) Has siblings	-0.174***	-0.094***	-0.092***	0.099	0.051	0.055
	(0.020)	(0.021)	(0.021)	(0.207)	(0.205)	(0.207)
(5) Bayleys mental development index (MDI) in baseline	0.001	0.001	0.001	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
(6) Weight for age z-score in baseline	0.016	0.014	0.016	0.085	0.101	0.099
	(0.013)	(0.012)	(0.012)	(0.075)	(0.078)	(0.077)
(7) Height for age z-score in baseline	0.007	0.005	0.004	-0.043	-0.052	-0.055
	(0.011)	(0.011)	(0.011)	(0.059)	(0.061)	(0.061)
Panel B: Household Characteristics						
(8) Age of mother above 25		-0.093***	-0.096***		-0.059	-0.048
		(0.022)	(0.022)		(0.122)	(0.123)
(9) Mother completed junior high		0.035	0.033		-0.382**	-0.366**
		(0.029)	(0.029)		(0.152)	(0.154)
(10) Father completed junior high		0.149***	0.146***		-0.132	-0.109
		(0.051)	(0.051)		(0.213)	(0.211)
(11) Father at home		-0.101***	-0.101***		0.475***	0.469***
		(0.021)	(0.021)		(0.127)	(0.128)
(12) Grandmother healthy		0.040*	0.038*		-0.017	-0.017
		(0.022)	(0.022)		(0.129)	(0.126)
(13) Grandmother completed primary school		0.196***	0.193***		-0.207	-0.204
		(0.035)	(0.035)		(0.132)	(0.133)
(14) Asset index		-0.006	-0.008		0.105*	0.105*
		(0.009)	(0.009)		(0.059)	(0.059)
(15) Household receives social security support under *Dibao*			-0.061***			0.332*
			(0.023)			(0.171)
(16) Constant	0.023	0.060	0.074			
	(0.086)	(0.084)	(0.084)			

Notes: Data source is author's survey. Columns 1-3 show coefficients and village cluster robust standard errors (in parentheses) from linear probability models where the dependent variable is 1 if a child's mother outmigrated at any point during the survey and zero otherwise. Columns 4-6 show marginal effects from ordered probit regressions where the dependent varaible is the wave (1 to 4) in which a child's mother was first found absent, using only the sample of children whose mothers ever migrate. All regressions control for recruitment cohort. * significant at 10%; ** significant at 5%; *** significant at 1%.

educated mothers, conditional on migrating at all during this time, tend to do so earlier (Columns 5-6, Row 9). Migrating mothers in higher asset households and households where the father did not migrate at baseline on the other hand tend to do so later (Rows 11 and 14).

The fact that receipt of *dibao* support (Row 15) is negatively correlated with migration and with later migration (conditional on mothers migrating at all) is of note. Although this could be a proxy for poverty, it remains significant even when controlling for household assets. While speculative, this could suggest that cash transfers under the *dibao* program reduce maternal out-migration in early childhood.

2.5 Empirical Strategy

The primary aim of this paper is to estimate the effects of maternal migration on ECD, nutrition, and health outcomes. As is clear from the discussion in Section 2.4, maternal migration decisions during early childhood are not random. A main concern when estimating the effects of maternal migration on child outcomes is therefore the endogeneity of the migration decision. That is, there may be unobserved factors that are correlated with both the migration of mothers and child outcomes. It could also be the case that there is reverse causality: mothers may be less likely to migrate if they feel that their children are lagging in their development or unhealthy. Although there is no indication that maternal migration is correlated with baseline child outcomes after controlling for other observables (Table 2, Rows 5-7), maternal perceptions may not be fully captured by these outcome measures.

Our main approach to estimate the effects of maternal migration is to take advantage of the longitudinal feature of our dataset and use child fixed effects to account for time-invariant observed and unobserved confounding factors. Accordingly, our identification strategy relies on the assumption that trends in the outcomes for children whose mothers do and do not migrate would be the same absent maternal migration. We test this assumption and other threats to credible identification below.

To implement this approach, we estimate variants of the regression:

$$\text{Outcome}_{it} = \alpha + \beta_1 \text{MigrantMother}_{it} + \beta_2 \text{C}_{it} + \beta_3 \text{H}_i + \eta_i + w_t + s_{it} + \varepsilon_{it} \tag{1}$$

in which Outcome_{it} is the outcome for child i in survey wave t, $\text{MigrantMother}_{it}$ is a dummy variable which is 1 if the mother of child i had migrated in the period preceding survey wave t; C_{it} is a vector of child characteristics including (depending on the specification) cohort fixed effects, a cubic of child age, gender, whether the child was premature, and whether the child has siblings; H_i is a vector of caregiver and household characteristics at baseline; η_i is a fixed effect for child i, w_t are survey wave indicators, s_{it} are enumerator effects designed to capture measurement error [7] and ε_{it} is an error term. Standard errors are clustered at the village level (thus accounting for correlation within villages as well as serial correlation over time – Bertrand, Duflo, and Mullainathan (2004)).

In addition to child fixed effects, we also estimate models controlling for lagged dependent variables. These lagged dependent variable estimates in combination with the fixed effect estimates are meant to provide bounds on the true causal effects (Guryan, 2001; Angrist and Pischke, 2008).[8] Specifically, the lagged dependent variable model estimate provides an upper bound on the true causal effect of maternal migration while the fixed effect estimate bounds the true effect from below.

To account for the fact that we estimate the effect of maternal migration on many outcomes, we calculate p-values adjusted for multiple hypothesis testing using the step-down procedure of Romano and Wolf (2005). We adjust separately across all 9 primary outcomes in the main analysis and across the 8 intermediate outcomes using 500 bootstrap repetitions. In tables presenting these results, we indicate the significance of coefficients at 1%, 5% and 10% levels post-adjustment.

3 Results

3.1 Primary Results

The primary results for the impact of maternal migration on early childhood outcomes are shown in Table 3. For each of the outcomes listed at left, we report the coefficient and standard error on the variable indicating migration of the mother estimated using four different variants of Equation 1. For each outcome, we show the estimated effect of maternal migration using OLS and controlling only for survey

[7] These include test administrator effects in regressions for Bayleys outcomes and nurse effects for hemoglobin and height and weight outcomes. Results are robust to exclusion of these effects, but are less precise.

[8] Guryan (2001) shows that if a treatment is positively selected on lagged outcomes or on fixed determinants of lagged outcomes then the difference-in-difference (fixed effect) estimate and lagged dependent variable model estimate bound the true causal effect (asymptotically).

wave and cohort fixed effects (Column 1), further controlling for additional child and household covariates (Column 2), additionally including a lagged dependent variable as a control (Column 3), and finally including child fixed effects, time varying control variables, and wave and cohort dummies (Column 4). Significance is indicated after adjusting for multiple hypotheses.

In the first column of OLS correlation results, we again see evidence of positive selection into migration in terms of child health outcomes. The coefficient on maternal migration is positive and significant for Hb concentration, anemia reduction, weight-for-age, height-for-age, and weight-for-height. Once additional child and household characteristics are controlled (Column 2), most of these positive correlations survive though the coefficients on height-for-age and the hemoglobin-based outcomes become insignificant. The estimated effect of maternal migration on cognitive development (Bayley MDI) on the other hand becomes significantly negative. These estimates however, are still potentially biased because they may fail to account for important sources of endogeneity.

Our main estimates using child fixed effects are shown in Column (4). Once time-invariant heterogeneity is accounted for, only the effect of maternal migration on cognitive development, as measured by the Bayley MDI sub-index, is statistically significant after adjusting for multiple outcomes (Row 1). We estimate that, on average without regard to differences in the timing of outmigration across the sample, maternal migration is associated with a 2.57 point reduction in MDI scores, or 0.15 sd. We estimate more easily interpretable effects accounting for the timing of migration and outcome measurement in Section 4.4 below.

We find no significant effects on psychomotor development, the probability of socioemotional delay, anemia, height, weight, or on the frequency of illness. This is some indication, however, of effects on linear growth and weight-for-height. There are small negative effects on height-for-age z-scores of 0.096 sd (Row 7) and positive effects of about the same magnitude on weight-for-height (0.107 sd, Row 8). These would reach significance without multiple hypothesis adjustments. While these two effects may seem at odds, they may result from remaining caregivers feeding children diets that are higher energy but lacking in micronutrients.

As an initial robustness check on these results, note that results are similar in lagged dependent variable models (Column 3) for the effects on weight-for-height and MDI scores (suggesting tight bounds around true effects), although the LDV

Table 3. Effect of maternal migration on ECD outcomes

		OLS	OLS	LDV	FE
		(1)	(2)	(3)	(4)
(1) Bayleys mental development index (MDI)		-1.023	-2.308**	-2.223***	-2.569**
		(1.039)	(0.971)	(0.917)	(1.100)
	N	*5395*	*5393*	*3578*	*5393*
(2) Bayleys psychomotor development index (PDI)		1.117	0.646	-0.078	1.477
		(0.981)	(0.985)	(0.934)	(1.252)
	N	*5377*	*5374*	*3554*	*5374*
(3) Socioemotional delay (1=yes; 0=no)		-0.002	-0.000	0.017	-0.020
		(0.023)	(0.021)	(0.021)	(0.032)
	N	*5517*	*5415*	*3651*	*5415*
(4) Hemoglobin concentration (g/L)		1.440**	0.534	-0.094	-0.692
		(0.646)	(0.607)	(0.565)	(0.805)
	N	*5284*	*5283*	*3459*	*5283*
(5) Anemic (Hb below 110 g/L)		-0.033*	-0.013	0.008	0.016
		(0.018)	(0.019)	(0.019)	(0.029)
	N	*5284*	*5283*	*3459*	*5283*
(6) Weight for age z-score		0.192***	0.161***	0.045**	0.021
		(0.055)	(0.053)	(0.022)	(0.030)
	N	*5349*	*5349*	*3525*	*5349*
(7) Height for age z-score		0.162**	0.110	0.021	-0.095
		(0.066)	(0.066)	(0.037)	(0.048)
	N	*5352*	*5352*	*3527*	*5352*
(8) Weight for height z-score		0.135**	0.138**	0.106***	0.108
		(0.054)	(0.054)	(0.039)	(0.055)
	N	*5369*	*5369*	*3549*	*5369*
(9) Times ill in past month		-0.045	-0.029	-0.017	-0.026
		(0.047)	(0.046)	(0.043)	(0.060)
	N	*5406*	*5406*	*3599*	*5406*
(10) Wave dummies		×	×	×	×
(12) Controls			×	×	×
(13) Control for lagged outcome				×	
(14) Child Fixed Effects					×

Notes: Data source is authors' survey. Table shows coefficients and standard errors on a variable indicating maternal absence for a majority of the previous six months in regressions with development and health outcomes at left as dependent variables. Column (1) shows the coefficient on maternal migration in an OLS regression pooling data across waves, controlling for survey wave dummies. Column (2) shows coefficients from pooled OLS regressions additionally controlling for baseline controls (a cubic in child age, gender, whether the child was premature, whether the child has siblings, maternal age, maternal educational level, paternal educational level, paternal migration status, health of the child's grandmother, the educational level of the child's grandmother, asset index, and whether the household receives social security support under *Dibao*). Column (3) controls for the once lagged value of the outcome variable along with wave dummies and baseline controls. Column (4) additionally controls for child fixed effects. All regressions with Bayleys MDI and PDI as dependent variables additionally control for tester fixed effects and regressions with health and nutrition outcomes as dependent variables additionally control for nurse fixed effects. Standard errors are clustered at the village level. *N* is the total number of observations in each regression. * indicates significance 10%; ** indicates significance at 5%; *** indicates significance at 1% after adjusting for multiple hypotheses using the step-down procedure of Romano and Wolf (2005) to control the familywise error rate (FWER).

estimates diverge from the FE estimates in the case of height-for-age.

3.2 Robustness Checks

There are three main threats to the validity of our results. The first is that, while child fixed effects accounts for time-invariant unobserved heterogeneity, there may remain time variant unobserved heterogeneity that biases our estimates. In other words, our estimates rely on the assumption that the outcomes of children whose mothers migrate in each period would have followed a trend similar to those who do not.

To test the plausibility of the common trend assumption, we compare the trends in each of our outcomes variables across children with migrating and non-migrating mothers in the periods before actual migration took place. Because we have four waves of data and mothers migrating between each wave, we can compare trends between never left-behind children and to-be-left-behind children across the initial three waves (between the first and second waves using children whose mothers migrate in the third wave and between the first and second and second and third waves for children whose mothers migrate in the fourth wave).

To conduct these tests, we regress each outcome on an indicator for whether a mother migrates in either the third or fourth survey wave, indicators for each of the first two survey waves, interactions between these, and control variables as in Equation (1) using only the sample of children whose mothers never migrate or migrate in waves 3 or 4. The results are shown in Appendix Table 1. For each outcome, we cannot reject that trends are the same for both types of children as indicated by the statistically insignificant coefficients on the interaction terms. This finding increases confidence that the parallel trend assumption is valid.

A second threat to the validity of our estimates comes from the potential endogeneity of maternal migration and attrition over time. In total, 29.6% of the children sampled in the baseline survey wave attrited from the sample at some point during the study and 16% attrited and were not recaptured in subsequent rounds. Although attrition of children from the sample is relatively small, it may be problematic if attrition is systematically correlated with maternal migration and child outcomes. Estimations based on the remaining panel would be biased.

To address this concern we first compare baseline characteristics of children who subsequently attrit and those who do not in Appendix Table 2. These comparisons

Appendix Table 1. Tests for parallel trends

Dependent variable:	Bayley MDI	Bayley PDI	Socioemotional delay	Hb (g/L)	Anemic	Weight for age z-score	Height for age z-score	Weight for Height	Times ill in past month
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(12)
(1) Mom ever left * Wave 2	-1.854	-1.827	-0.026	1.842	-0.039	0.032	0.085	-0.042	-0.009
	(1.794)	(2.267)	(0.054)	(1.270)	(0.052)	(0.049)	(0.091)	(0.096)	(0.105)
(2) Mom ever left * Wave 3	-1.051	-1.357	0.058	1.144	-0.044	-0.006	0.155	-0.118	-0.028
	(2.290)	(2.339)	(0.060)	(1.346)	(0.056)	(0.053)	(0.102)	(0.094)	(0.095)
(3) Wave 2	6.314	12.778**	-0.085	9.173***	-0.195*	0.172	0.569**	-0.312	-0.395
	(5.062)	(5.676)	(0.124)	(3.007)	(0.109)	(0.141)	(0.246)	(0.213)	(0.290)
(4) Wave 3	6.379	24.450**	-0.293	16.371***	-0.392*	0.397	1.269***	-0.669	-0.745
	(9.643)	(11.028)	(0.238)	(5.782)	(0.210)	(0.281)	(0.474)	(0.420)	(0.569)
(5) *N*	3693	3682	3700	3643	3643	3665	3667	3681	3699

Notes: Data source is author's survey. In the regressions where the dependent variable is Bayley MDI, Bayley PDI, controls for Bayley tester also included. Regressions for Hb, Anemia, Weight for age z-score, Height for age z-score, Weight for height additinally control for administering nurse. Robust standard errors clustered at the village level are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table 2. Summary statistics of outcomes and covariates by attrition status.

	Full Sample	Attrited sample	Non-attrited sample	Difference: (2)-(3)
	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)	*P*-value
	(1)	(2)	(3)	(4)
Panel A: Development outcomes				
(1) Bayleys mental development index (MDI)	96.574	97.235	96.179	0.289
	(16.952)	(16.794)	(17.042)	
(2) Cognitively delayed (Bayley MDI below 80)	0.142	0.127	0.151	0.195
	(0.349	(0.332)	(0.358)	
(3) Bayleys psychomotor development index (PDI)	89.862	91.231	89.046	0.016
	(17.373)	(16.391)	(17.892)	
(4) Psychomotor development (Bayley PDI below 80)	0.241	0.202	0.265	0.004
	(0.428)	(0.402)	(0.442)	
(5) Socioemotional delay (1=yes; 0=no)	0.393	0.386	0.397	0.652
	(0.489)	(0.487)	(0.490)	
Panel B: Health outcomes				
(6) Hemoglobin concentration (g/L)	108.644	108.798	108.553	0.826
	(12.652)	(12.595)	(12.691)	
(7) Anemic (Hb less than 110 g/L)	0.510	0.495	0.520	0.432
	(0.500)	(0.500)	(0.500)	
(8) Weight for age z-score	0.347	0.374	0.331	0.515
	(0.993)	(1.034)	(0.969)	
(9) Height for age z-score	0.104	0.163	0.069	0.179
	(1.182)	(1.177)	(1.184)	
(10) Weight for height z-score	0.357	0.344	0.364	0.686
	(1.144)	(1.201)	(1.109)	
(11) Times ill in past month	1.083	1.043	1.107	0.261
	(0.982)	(0.943)	(1.004)	
Panel C: Child Characteristics				
(12) Age of child (months)	8.888	8.842	8.916	0.320
	(1.851)	(1.883)	(1.833)	
(13) Female	0.471	0.455	0.480	0.504
	(0.499)	(0.498)	(0.500)	
(14) Premature birth	0.113	0.109	0.115	0.716
	(0.323)	(0.328)	(0.319)	
(15) Has siblings	0.229	0.163	0.268	0.000
	(0.420)	(0.370)	(0.443)	
Panel D: Household Characteristics				
(16) Age of mother above 25	0.524	0.497	0.540	0.162
	(0.500)	(0.500)	(0.499)	
(17) Mother completed junior high	0.166	0.185	0.154	0.169
	(0.372)	(0.388)	(0.361)	
(18) Father completed junior high	0.055	0.067	0.049	0.303
	(0.229)	(0.250)	(0.215)	
(19) Father at home	0.467	0.432	0.488	0.048
	(0.499)	(0.496)	(0.500)	
(20) Grandmother healthy	0.406	0.402	0.408	0.875
	(0.491)	(0.491)	(0.492)	
(21) Grandmother completed primary school	0.156	0.151	0.159	0.623
	(0.363)	(0.359)	(0.366)	
(22) Asset index	-0.011	0.038	-0.040	0.199
	(1.193)	(1.178)	(1.201)	
(23) Household receives social security support under *dibao*	0.245	0.262	0.235	0.176
	(0.430)	(0.440)	(0.425)	

Notes: Data source is authors' survey. Descriptive statistics of child and houshold characteristics when children 6-12 months of age. The first column shows the mean and standard deviation of each characteristic for the full sample; column 2 shows statistics for children and households where the mother does not migrate during the study period; column 3 shows statistics for children and households where the mother migrates at some point before children are 30-36 months of age. Socioemotional delay determined using the Ages and Stages: Socio-Emotional (ASQ:SE) questionnaire. Father at home is 1 if the father has been at home for a majority of the past six months and zero otherwise. Whether grandmother is healthy based on self-reported general health on 1-5 likert scale. Asset index constructed using polychoric principal components on the following variables: tape water, toilet, water heater, wash machine, computer, internet, fridge, air condition, motor or electronic bycicle, and car.

show that these two groups are largely similar. While this is reassuring, we also re-estimate our main individual fixed effect regressions reweighting observations to give more weight to those less likely to remain in the sample (and thus attempting to restore representativeness of the sample – Wooldridge (2010)). First, we estimate the probability children remained in our sample as a function of baseline characteristics. Using these estimated coefficients, we then predict the probability that each child remains in the sample. Finally, we re-weight the regressions using the inverse of the predicted probability. The results of this exercise (shown in Appendix Table 3), suggest that effects on cognition are robust to attrition bias. Effects on anthropometric indicators, however, attenuate slightly.

A third concern is regarding the definition of maternal migration. Following previous literature, our main results consider a mother to have migrated if they have been absent for more than half of the preceding six months before the survey. However, this definition may fail to adequately capture migration behavior. In Appendix Table 4, we show robustness of our primary results to alternative definitions a maternal migration using 25% and 75% of the preceding time period. Results using these alternative definitions are consistent with the main results for MDI, height-for-age and weight-for-height.

3.3 Intermediate Outcomes

Table 4 shows fixed effects estimates of the impact of maternal migration on intermediate outcomes. Panel A shows effects on parenting activities – investments in cognitive and emotional development. Panel B shows effects on indicators of feeding behavior. Significance is indicated after adjusting for multiple hypotheses.

We find that a child's mother migrating leads to a reduction in adult time engaged in stimulating activities with children. We find an 8 percentage point reduction in the number of caregivers reporting that they used toys to play with the child in the previous day (Column 1). We also find a 10 percentage point reduction in caregivers saying that they sang songs to children the previous day (Column 4). These estimates imply that reduced caregiver engagement in stimulating activities with the child may contribute to the negative effects of maternal migration on cognition scores that we find above.

In Panel B, we see that maternal migration has clear negative effects on nutritional quality. We find no distinguishable effects on the index of meal frequency (a measure

Appendix Table 3. Effects of Maternal Migrationon on ECD Outcomes, Reweighted for Probability of Attrition

		OLS	OLS	LDV	FE
		(1)	(2)	(3)	(4)
(1) Bayleys mental development index (MDI)		-1.054	-2.416**	-2.316**	-2.524**
		(1.035)	(0.966)	(0.911)	(1.100)
	N	*5395*	*5393*	*3578*	*5393*
(2) Bayleys psychomotor development index (PDI)		1.348	0.768	0.112	1.799
		(0.995)	(0.976)	(0.933)	(1.238)
	N	*5377*	*5374*	*3554*	*5374*
(3) Socioemotional delay (1=yes; 0=no)		0.002	0.001	0.017	-0.021
		(0.022)	(0.021)	(0.021)	(0.032)
	N	*5517*	*5415*	*3651*	*5415*
(4) Hemoglobin concentration (g/L)		1.407**	0.536	-0.088	-0.714
		(0.647)	(0.613)	(0.566)	(0.820)
	N	*5283*	*5283*	*3459*	*5283*
(5) Anemic (Hb below 110 g/L)		-0.035*	-0.014	0.006	0.014
		(0.018)	(0.019)	(0.019)	(0.030)
	N	*5283*	*5283*	*3459*	*5283*
(6) Weight for age z-score		0.191***	0.162***	0.045**	0.025
		(0.055)	(0.054)	(0.021)	(0.030)
	N	*5349*	*5349*	*3525*	*5349*
(7) Height for age z-score		0.174**	0.126*	0.025	-0.077
		(0.067)	(0.067)	(0.037)	(0.049)
	N	*5352*	*5352*	*3527*	*5352*
(8) Weight for height z-score		0.123**	0.126**	0.101**	0.096*
		(0.054)	(0.054)	(0.040)	(0.055)
	N	*5369*	*5369*	*3549*	*5369*
(9) Times ill in past month		-0.040	-0.029	-0.014	-0.021
		(0.047)	(0.047)	(0.044)	(0.062)
	N	*5406*	*5406*	*3599*	*5406*
(10) Wave dummies		×	×	×	×
(12) Controls			×	×	×
(13) Control for lagged outcome				×	
(14) Child Fixed Effects					×

Notes: Data source is authors' survey. Table shows coefficients and standard errors on a variable indicating maternal absence for a majority of the previous six months in regressions with development and health outcomes at left as dependent variables. These regressions are analogous to Table 3, but regressions are reweighted using probability that children remained in sample. Column (1) shows the coefficient on maternal migration in an OLS regression pooling data across waves, controlling for survey wave dummies. Column (2) shows coefficients from pooled OLS regressions additionally controlling for baseline controls (a cubic in child age, gender, whether the child was premature, whether the child has siblings, maternal age, maternal educational level, paternal educational level, paternal migration status, health of the child's grandmother, the educational level of the child's grandmother, asset index, and whether the household receives social security support under Dibao). Column (3) controls for the once lagged value of the outcome variable along with wave dummies and baseline controls. Column (4) additionally controls for child fixed effects. All regressions with Bayleys MDI and PDI as dependent variables additionally control for tester fixed effects and regressions with health and nutrition outcomes as dependent variables additionally control for nurse fixed effects. Standard errors are clustered at the village level. N is the total number of observations in each regression. * indicates significance 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Appendix Table 4. Alternative Definitions of Migration

Alternative definition of migration:	Gone 75% of previous six months (1)	Gone 50% of previous six months (2)	Gone 25% of previous six months (3)
(1) Bayleys mental development index (MDI)	-1.948*	-2.569**	-2.162**
	(1.025)	(1.100)	(1.006)
N	*5393*	*5393*	*5393*
(2) Bayleys psychomotor development index (PDI)	0.875	1.477	0.506
	(1.232)	(1.252)	(1.174)
N	*5347*	*5347*	*5347*
(3) Socioemotional delay (1=yes; 0=no)	-0.007	-0.020	-0.009
	(0.030)	(0.032)	(0.033)
N	*5415*	*5415*	*5415*
(4) Hemoglobin concentration (g/L)	0.374	-0.692	-1.576**
	(0.800)	(0.805)	(0.715)
N	*5283*	*5283*	*5283*
(5) Anemic (Hb below 110 g/L)	-0.012	0.016	0.052**
	(0.028)	(0.029)	(0.026)
N	*5283*	*5283*	*5283*
(6) Weight for age z-score	0.006	0.022	0.023
	(0.029)	(0.030)	(0.028)
N	*5349*	*5349*	*5349*
(7) Height for age z-score	-0.076*	-0.095**	-0.077
	(0.045)	(0.048)	(0.047)
N	*5352*	*5352*	*5352*
(8) Weight for height z-score	0.071	0.108*	0.096**
	(0.049)	(0.055)	(0.048)
N	*5369*	*5369*	*5369*
(9) Times ill in past month	-0.027	-0.026	-0.058
	(0.057)	(0.060)	(0.056)
N	*5406*	*5406*	*5406*

Data source is authors' survey. Table shows coefficients and standard errors on a variable indicating maternal absence during the previous six months in regressions (specified as in equation 1) with development and health outcomes at left as dependent variables. In column (1) maternal absence is 1 if mothers were away more than 75% of the previous six months. In column (2) maternal absence is 1 if mothers were away for more than 50% of the previous six months (our primary definition used in the main analysis shown in Table 3). In column (3) maternal absence is 1 if mothers were away more than 25% of the previous six months. All regressions control for wave dummies, cubic in child age, and child fixed effects. Regressions with Bayleys MDI and PDI as dependent variables additionally control for tester fixed effects and regressions with health and nutrition outcomes as dependent variables additionally control for nurse fixed effects. Standard errors are clustered at the village level. N is the total number of observations in each regression. * indicates significance 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Table 4. Fixed Effect Estimates for the Effect of Maternal Migration on Intermediate Outcomes

Panel A: Stimulation	Used toys to play with baby yesterday	Told stories to baby yesterday	Read to baby yesterday	Sang to baby yesterday
	(1)	(2)	(3)	(4)
Migrant Mother	-0.080**	-0.023	-0.001	-0.100***
	(0.039)	(0.022)	(0.014)	(0.033)
N	*4591*	*4590*	*4590*	*4590*

Panel B: Diet	Minimum meal frequency	Dietary diversity	Minimum dietary diversity	Iron rich foods
	(1)	(2)	(3)	(4)
Migrant Mother	-0.008	-0.231**	-0.060*	-0.168***
	(0.034)	(0.111)	(0.036)	(0.064)
N	*4082*	*4559*	*4559*	*5360*

Notes: Data source is authors' survey. All regressions control for child fixed effects and wave fixed effects. Robust standard errors (in parentheses) are clustered at the village level. For breastfed children age 6-8 months minimum meal frequency is 1 if fed twice the previous day; for children 9-11 months, meal frequency is 1 if fed three or more times per day, and for non-breasfed children 6 months and above, minimum meal frequency is 1 if fed four or more times per day. Dietary diversity is the number of the following food categories fed to the child the previous day: grains, legumes, meat, dairy, eggs, foods rich in vitamin A, and fruit. Minimum dietary diversity is 1 if dietary diversity is 4 or more. Iron rich foods include meat, fruit, vegetables, and iron supplements. N is the total number of observations in each regression. * indicates significance 10%; ** indicates significance at 5%; *** indicates significance at 1% after adjusting for multiple hypotheses using the step-down procedure of Romano and Wolf (2005) to control the familywise error rate (FWER).

of quantity – Column 1), but find significant negative effects on dietary diversity and on the feeding of iron-rich and foods that promote iron absorption (meat, green leafy vegetables, iron supplements, and fruit – Columns 2-4). That we find no effects on hemoglobin concentration or anemia, however, indicates that reductions in iron rich foods may not be severe enough (yet) to increase risk of iron deficiency. A reduction in the consumption of micronutrients is a plausible explanation for negative effects on linear growth (Rivera et al., 2003). Previous studies have also noted large differences in nutritional knowledge between parents and grandparents in rural China, particularly regarding micronutrient needs for young children (Tan et al., 2010).

3.4 Timing of Outmigration

Our primary estimates of the impact of maternal migration estimate the average effect of maternal migration on child outcomes without regard to when mothers left. We estimate what the effect is when mothers leave at some point during the first two years, but these estimates do not consider how effects may vary depending on when mothers migrate. Given rapid developmental changes at this age and evidence of relatively short time periods of high sensitivity to environmental changes, however, when mothers choose to migrate may have varying effects.

To address this question, we report child fixed effect regressions using subsamples of the data chosen to isolate treatment effect heterogeneity by the timing of maternal migration and the timing of the outcome measure. That is, we re-estimate the primary fixed effects regressions but using only two waves of data at a time and including only left-behind children whose mother migrate at a single point in time.

The results of this exercise are reported in Table 5. For each outcome for which we find significant or marginally significant effects in the main analysis, we show six different estimates by the age of migration and age of the measured outcome. The first three columns show estimates for the effect of mothers migrating between the first and second survey wave ("period 1") on outcomes at 12-18 months, 18-24 months, and 24-30 months of age. The next two columns show estimates for impacts for mothers migrating between the second and third waves ("period 2") on outcomes at 18-24 months and 24-30 months. The final column shows the estimated impacts of maternal migration between the third and fourth waves ("period 3") on outcomes at 24-30 months.

Table 5. Effects by timing of maternal migration

When mother left:	Period 1			Period 2		Period 3
Outcome at:	12-18 mo.	18-24 mo.	24-30 mo.	18-24 mo.	24-30 mo.	24-30 mo.
	(1)	(2)	(3)	(4)	(5)	(6)
(1) Bayleys mental development index (MDI)	-5.142**	-3.868	-5.238*	-2.363	1.422	-4.326*
	(2.121)	(2.397)	(2.672)	(2.544)	(2.680)	(2.558)
N	*2380*	*2375*	*2381*	*2318*	*2325*	*2403*
(2) Height for age z-score	-0.163	-0.157*	-0.061	-0.051	-0.180	0.038
	(0.110)	(0.091)	(0.099)	(0.120)	(0.131)	(0.107)
N	*2366*	*2362*	*2370*	*2303*	*2311*	*2389*
(3) Weight for Height	0.208*	0.204*	0.037	0.020	0.193	-0.006
	(0.107)	(0.113)	(0.119)	(0.147)	(0.175)	(0.103)
N	*2376*	*2367*	*2372*	*2308*	*2313*	*2391*

Notes: Data source is authors' survey. Table shows coefficients and standard errors on a variable indicating maternal absence for a majority of the previous six months in regressions with outcomes at left as dependent variables. All regressions control for child and wave fixed effects and a cubic term in child age. Regressions in row (1) additionally control for Bayley tester and those in rows (2) and (3) additionaly control for the nurse taking measurements. Standard errors are clustered at the village level. N is the total number of observations in each regression. * indicates significance 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Despite a significant reduction in power compared to the main estimates, there are a number of informative results. First, maternal migration during period 1 has strong effects on outcomes soon after mothers migrate. However, the effects on nutritional outcomes appear to dissipate as children age and are negligible by the time children are 24-30 months old. On the other hand, effects on cognitive development are more persistent. We estimate that mothers migrating in the first period reduces scores on the Bayleys MDI at 24-30 months of age by 5.24 points (or 0.31 sd) (Column 3, Row 1). For comparison, recent intensive parenting interventions in Colombia and China increased largely comparable measures of cognitive development by around 0.25 standard deviations (Attanasio et al., 2014; Sylvia et al., 2016). The effect of migration in this early period on children at 2-2.5 years of age is significantly more negative than the effect of migration six months later in period 2 (Column 5). The last column in the table shows that there is an effect on cognition at 2-2.5 years of migration during the period immediately before. Overall, these results are consistent with earlier migration being more detrimental to longer term cognitive development but there also being immediate negative effects of maternal migration.

4 Conclusion

In this paper, we study the effects of maternal migration on the development, health and nutrition outcomes of infants and toddlers in rural China. Using a unique panel survey following children from six months of age for two years, we find that maternal migration during early childhood significantly reduces cognitive development and has negative effects on nutrition. We also find that early migration (before children are 15 months old) has large and persistent effects on cognitive development, reducing cognitive scores by 0.31 sd when children are 2-2.5 years old.

Our study faces a number of limitations that should be addressed in future research. First, it is possible that we do not fully address endogeneity. Although we believe we are able to account for the most important sources of endogeneity using child fixed effects, it is possible that time variant unobserved heterogeneity remains. Shocks, for example, that affect both the probability that mothers migrate and child outcomes could affect the validity of our estimates. This concern may be mitigated, however, by the reduced potential for shocks to affect our results given the relatively short time span of data collection. Future studies could address this issue with instrumental variables, unfortunately appropriate instruments were unavailable for this context. Second, we were unable to examine effects of paternal migration (although we control for paternal migration status at baseline). Previous studies have suggested deferring effects of maternal and paternal migration for older children; how these effects differ for younger children is an important question. Nevertheless, from other contexts suggests that the effect of maternal migration is likely to be more important in early childhood. Finally, our sample was drawn from a poor region of rural China. Results may not extend to other contexts.

Despite these caveats, we believe these results have a number of important implications for policy makers in China. The main message is that the migration that has helped to fuel China's growth may have come with a cost in terms of lost human capital for the next generation. To mitigate these costs, investments should be made to support ECD in rural areas (though these should take into account potential effects on parental migration decisions – Myerson (2016)). It is important to note however that, although we find migration negatively effects the outcomes of left-behind children, a large fraction of all rural children have delayed development outcomes. In the final wave of our survey, 52% of toddlers were delayed in their cognitive or psychomotor development (having Bayleys MDI or PDI measures<80) regardless of migration status. Thus, investments are need for all children, not just those left behind. Another policy option may be cash transfers targeting households with young children, either unconditional or conditional on mothers delaying outmigration. Future research should focus on evaluating the relative cost effectiveness of policy alternatives.

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