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Restrictions on Migration Create Gender Inequality: The Story of China's Left-Behind Children

Xuwen Gao
Peking University, gaoxw@phbs.pku.edu.cn

Wenquan Liang
Jinan University, liang.wenquan@jnu.edu.cn

Ahmed Mushfiq Mobarak
Yale University, ahmed.mobarak@yale.edu

Ran Song
National University of Singapore, ran.song@yale-nus.edu.sg

Restrictions on Migration Create Gender Inequality: The Story of China's Left-Behind Children *

Xuwen Gao Wenquan Liang Ahmed Mushfiq Mobarak Ran Song

Abstract

About 11% of the Chinese population are rural-urban migrants, and the vast majority of them (124 million people) possess a rural *hukou* which severely restrict their children's access to urban public schools. As a result, 61 million children are left behind in rural areas. We use a regression-discontinuity design based on school enrollment age cutoffs to document that migrants are significantly more likely to leave middle-school-aged daughters behind in poor rural areas *without either parent present* when schooling becomes expensive, compared to middle-school-aged sons. The effect is larger when the daughter has a male sibling. Migrant parents send significantly less remittances back to daughters than sons. Migrants from rural areas adjacent to cities with more restrictive *hukou* policies are more likely to separate from children as new job opportunities arise in nearby cities due to trade-induced shocks to labor demand. This produces a shift-share IV strategy, when paired with a longitudinal dataset shows that those children complete 3 fewer years of schooling, are 41% more likely to fail high school entrance exams, have worse mental and physical health, and remain poor as adults. Although China's *hukou* mobility restrictions are not gender-specific in intent, they have larger adverse effects on girls.

Keywords: Migration, *hukou*, Left-Behind Children, Gender Inequality

JEL Codes: J13, J16, R23

*Xuwen Gao: Peking University, gaoxw@phbs.pku.edu.cn. Wenquan Liang: Jinan University, liang.wenquan@jnu.edu.cn. Ahmed Mushfiq Mobarak: Yale University, NBER, Deakin University, ahmed.mobarak@yale.edu. Ran Song: National University of Singapore, ran.song@yale-nus.edu.sg.
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1 Introduction

People leaving rural areas to go work in factories located in cities has been an important engine of growth in rapidly developing countries like China. 11% of the Chinese population in the 2005 census – 145 million people – were rural-urban migrants. The rapid urbanization generates a complex set of social and economic effects on both the cities migrants move into, and the places they leave behind. Family separation is an important aspect of the societal disruption that accompanies structural transformation and urbanization. As parents move to cities in search of employment, they often leave their children behind under the care of others. This can have gendered effects if migration, remittance, and leave-behind choices differ between the parents of sons versus daughters.

These choices can hold large consequences for the country's development pathways, because of the massive scale of this issue. 69 million Chinese children were growing up in rural areas without parents in 2015, left behind when their parents migrated (UNICEF, 2018). This represents 30 percent of all children born in rural areas (Chen, 2013). We show that this issue is the result of a conscious policy choice: China imposes internal mobility restrictions that undermine parents' ability to migrate with their children. In particular, stringent *hukou* restrictions in many Chinese cities can make it prohibitively expensive or even impossible for in-migrants to bring their children with them and enroll them in urban schools. Of the 145 million rural-urban migrants in the 2005 census, the vast majority (124 million) were unskilled migrants with a rural *hukou*, which implies that they would have to pay a large fee called $zanzhufei$ to enroll their children in a public school in the city. $Zanzhufei$ for junior middle school enrollment is about 10% of the average migrant's earnings, which acts as a big financial deterrent. Such constraints on migrant parents are becoming even more acute over time as cheaper schools specifically designated for migrant children are shut down in Beijing and other popular migration destinations (Yang, 2016).

We use variation in the stringency of *hukou* restrictions in cities where migrant parents work to analyze how parents decide whether and when to leave their children behind in rural areas. Schooling is compulsory, and children must transition from primary school to junior middle school around the age of 12 or 13, depending on their month of birth. *Zanzhufei* for junior middle school is 53% larger than for primary school, which changes parents' incentives and ability to keep their children with them in the city exactly at that age. We employ a regression discontinuity research design based on the age cutoff for middle school entry using data on the exact date of birth of 173,468 children of migrants, to study whether sons or daughters are treated any differently when parents make migration choices. We show that parents who had migrated to cities with stringent *hukou* restrictions are about 3.5 percentage points (10%) more likely to leave their daughters behind in the rural area exactly when daughters transition into middle school age. These daughters are most frequently left behind without either parent present. That same discontinuity at that age cutoff does not exist for sons. The discontinuity also does not exist for girls whose parents had migrated to less-*hukou*-restrictive cities.[1] Gender gaps in schooling widen across the world as children enter secondary schools (Muralidharan and Prakash, 2017), and our results are consistent with that pattern.

To further address any selection issues arising from parents' destination choices, we study the effects of a 2014 policy in which the central government urged "mega cities" - defined as those with a population of over five million in the city central district area - to rigidly control the population. This new "migrant population control policy" led to a tightening of *hukou* restrictions and shutting down on migrant schools in mega cities (Figure A1). We find that parents who had previously migrated to cities above the 5-million-population cutoff become 7 percentage points more likely to leave their middle-school-aged daughter behind after 2014, relative to parents who had previously migrated to cities below the "mega-city" population cutoff. The effect is robust when we restrict attention to migrants who had made their destination choices before the 2014 policy was announced. That same discontinuity does not exist for boys.

Thus, using a different research design and very different variation in the data, we again find that although China's policy of mobility restrictions is not gender-specific in its intent or design, it produces a gendered effect in which daughters of a certain

[1] Migrant parents' destination choices may depend on the importance parents place on their child's education. Our triple difference set-up (by *hukou* policy stringency, by middle school age cutoff, and by gender of child) helps mitigate this endogeneity concern.

age become more likely to be separated from their parents.

If migrating for work improves parents' earnings capacity, that could benefit children left behind even if parents are unable to spend time with them (Yang, 2008). The net effect on children depends whether the parents' time or money is more important for the child's human capital accumulation (Zhang et al., 2014). We therefore add two pieces of analysis to better understand the lives of children left behind. First, we analyze migrant parents' remittance behavior, and find that migrants who leave daughters behind remit 9% less than migrants who leave sons behind. Girls therefore receive less parental time as well as less money compared to boys.

Second, we use a longitudinal survey that tracks rural children from Gansu province over 15 years to analyze the long run consequences of being left behind on later-life outcomes. This survey allows us to identify up to 2000 junior-middle-school-aged children growing up in rural area either with or without their parents. Since the parents' decision to migrate (leaving their child behind) is not random, we instrument that choice using global import demand shocks that raises labor demand in cities near each rural area (Khanna et al., 2021), interacted with the *hukou* policy stringency of those cities. This interaction term identifies the migration-pull to the types of cities where parents find it very difficult to take their children with them. This analysis shows that growing up without parents has adverse effects on the child's human capital accumulation, and on their socioeconomic achievements as adults. Children whose parents migrated and left them behind complete three fewer years of schooling and are 40 percentage points more likely to end up in the lowest income quartile as adults, compared to children whose parents remain with them in the rural hometown.[2]

While these effects are large, they are likely conservative estimates of the true costs of parental separation for two reasons. First, we can only compare children who were left behind with children who were living with parents *in the village* in our longitudinal data, while the comparison group in the first part of our paper are migrant children growing up *in the city*. Parents trapped in rural areas earn 60% less than migrant parents (2005 census), and left-behind children fare worse than even this

[2]An alternative estimation strategy in which we instrument parents' decision to migrate with rainfall shocks in the rural area interacted with historical migration ties due to presence of urban visitors in that rural area in 1982 (e.g. due to the Mao-era send-down movement) produces very similar results.

relatively disadvantaged group. Second, our instrument - increases in labor demand in nearby cities - should otherwise benefit rural children by improving their family's socioeconomic status and creating future economic opportunities. Especially children whose parents migrate and create a link to that growing city should benefit most. Despite those other positive channels of impact, we estimate detrimental effects on children left-behind, on net. The cost imposed by the parental separation channel is therefore likely even larger than what we document.

Taken together, our results suggest that girls suffer disproportionately when strict mobility restrictions are imposed on migrant workers in a rapidly developing and urbanizing society. When it is expensive for migrants to keep their children with them, they are more likely to separate from daughters than sons, and daughters receive less time, attention, and money from their parents. This undermines their human capital accumulation and hurts girls throughout their lives.

These gendered effects can be traced back to a conscious policy choice of imposing restrictions on people's mobility. That issue is not only restricted to China; '*hokhau*' policy in Vietnam also makes it similarly difficult for migrant children to be enrolled in public schools at their parents' work locations (Cameron, 2012). Rich countries that host cross-border migrant workers but discourage those migrants from bringing family members with them (Mobarak et al., forthcoming) may also produce such distributional effects.

Other research has examined the effects of migration on children's educational outcomes (Zhang et al., 2014), but we are among the first to document the long-run consequences in adulthood, and the first – to the best of our knowledge – to document these gendered effects, and connect it to mobility restrictions. We add to the literature on the sources of gender disparities[3] by identifying a new mechanism by which gender disparities might emerge even if the underlying policy (of mobility restrictions) has no direct, explicit gender dimension. We also contribute to the literature on the adverse welfare effects of spatial immobility (Gollin et al., 2014; Bryan et al., 2014; Khanna et al., 2021), and add a gender dimension to the distributional consequences

[3] Beaman et al. (2012); Blau and Kahn (2017); Card et al. (2016); Goldin (2014); Goldin et al. (2021); Barth et al. (2017); Hannum et al. (2022); Qian (2008); Bhalotra et al. (2019); Dahl and Moretti (2008); Chetty et al. (2016).

of migration restrictions.

The remainder of this paper proceeds as follows. Section 2 describes the data and Section 3 discusses stylized facts about the *hukou* system and left-behind children in China. Section 4 provides RD estimates of how *hukou* restrictions result in school-aged girls being left behind, Section 5 presents the long-term economic consequences associated with leaving children behind and Section 6 discusses the potential mechanisms driving our empirical pattern. Section 7 concludes.

2 Institutional Background

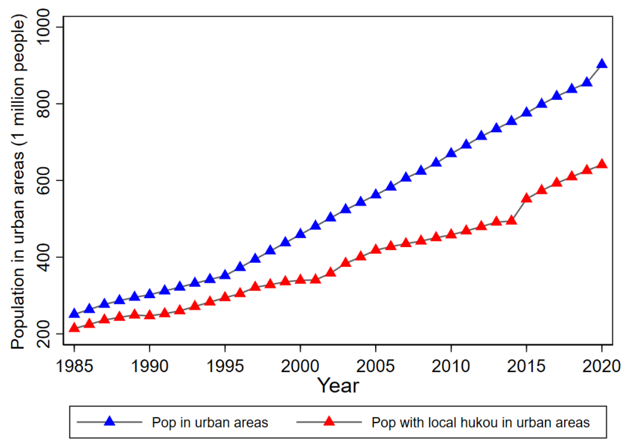
2.1 Hukou Restrictions, Migration, and Children Left behind

In 1958, China formally instituted the *hukou* system to control internal migration. The system required that each person be classified as rural or urban and be assigned a locality of *hukou* registration, which is typically the person's location of birth. One's *hukou* registration determines one's entitlement to pursue many activities, and eligibility for state-provided goods and services in a specific place. All internal migration was subject to approval from local authorities at the destination. Thus, the red *hukou* book served as an internal passport that determines a person's rights to reside and work in specific locations within China. Children (regardless of age and gender) inherit their parents' hukou status, including any new urban *hukou* their parent may obtain.

These mobility restrictions have been gradually relaxed since 1984. Chinese citizens can now migrate to cities, but lack of an urban *hukou* limits their access to many government-provided benefits at the destination. Most importantly, it is difficult and expensive for the children of migrant parents to enter urban public schools.

Economic growth in China triggered a dramatic increase in rural-urban migration. With an influx of rural migrants, the population of Chinese cities surged from 200 million in 1985 to 900 million in 2020 (Figure 1). Only a subset of those migrants were granted urban *hukou*, so the number of urban residents without urban *hukou* privileges also increased dramatically during this period. Obtaining an urban *hukou* requires levels of professional skills or educational attainment that are very difficult for the vast majority of rural migrants to attain (Khanna et al., 2021). The schooling restrictions have therefore led to large increases in the number of children left behind in rural areas. In 2018, approximately thirty percent of all children in rural China (69 million children) were growing up without their parents (UNICEF, 2018).

Figure 1: More and More People Don't Have Local Urban *Hukou* as China Urbanizes



Note: The blue line denotes the population in urban areas, and the red line shows the population holding local urban *hukou* in urban areas. Data come from the *China Statistical Yearbook*.

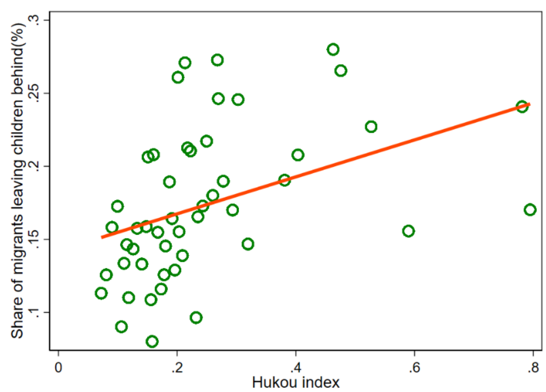
The stringency of *hukou* regulations varies, with more developed cities with better amenities placing more restrictions on migrants. Figure 2 illustrates that the stringency level of *hukou* restrictions is positively correlated with the share of rural migrants who leave their kids behind. There are many clear indications that left-behind rural children experience worse educational quality: teachers in rural schools have lower educational attainment (Table A2), are less professionally accomplished (Table A3), and have access to worse facilities (Table A4) than their counterparts in urban schools.

To keep their school-aged children in urban schools, migrant parents either have to pay an extra fee called *zanzhufei*, or send their children to "migrant schools" set up in cities specifically for poor migrant children without a local *hukou*. These schools are also of poorer quality than urban public schools.[4] Many cities closed migrant schools

[4]The majority of teachers in migrant schools do not have adequate credentials or experience to obtain jobs in city public schools. Migrant schools are often overcrowded and have worse infrastructure They charge fees that are expensive for migrants, but much lower than *zanzhufei* charged by public schools for migrant students.

in recent years (Table A5), which forces parents to pay steeper *zanzhufei* if they want to keep their children, and this can be prohibitive for poor migrant households. The amount of *zanzhufei* is higher in cities that have more stringent *hukou* restrictions (Figure 3), which is why *hukou* policy stringency is a useful measure of the difficulty migrant parents face in keeping their children with them.

Figure 2: *Hukou* Index and the Share of Migrants Leaving Children Behind

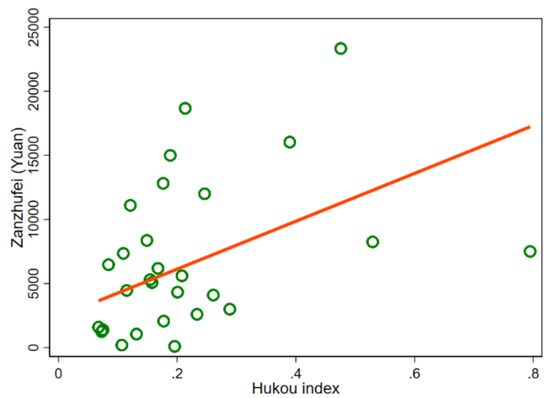


Notes: This figure shows the relationship between the share of migrants leaving children behind and the stringency of *hukou* regulations in migrants' destination cities. Cities are grouped into fifty groups according to the quantile of the *hukou* index. The vertical axis denotes the mean value of the share of migrants leaving children behind and the horizontal axis denotes the mean value of the *hukou* index in each quantile. Data on left-behind children come from the *China Migrants Dynamic Survey (CMDS)*, and data on the *hukou* index come from Zhang et al. (2019).

2.2 Junior Middle Schools More Restricted than Primary Schools

Education is compulsory in China. By law, parents must enroll their children in primary school if they turned six by September 1 in a given year and must enroll them in junior middle school if they turn 12 by that day. *Hukou*-policy based restrictions are a much bigger constraint on migrant families with junior middle school aged children relative to primary-school-age. Junior middle schools charge a substantially higher amount of zanzhufei than primary schools (Table A6). The number of available school seats is more limited in urban junior middle schools compared to primary schools.

Figure 3: *Hukou* Restrictions and *Zanzhufei* (Extra School Fee) for Migrants' Children



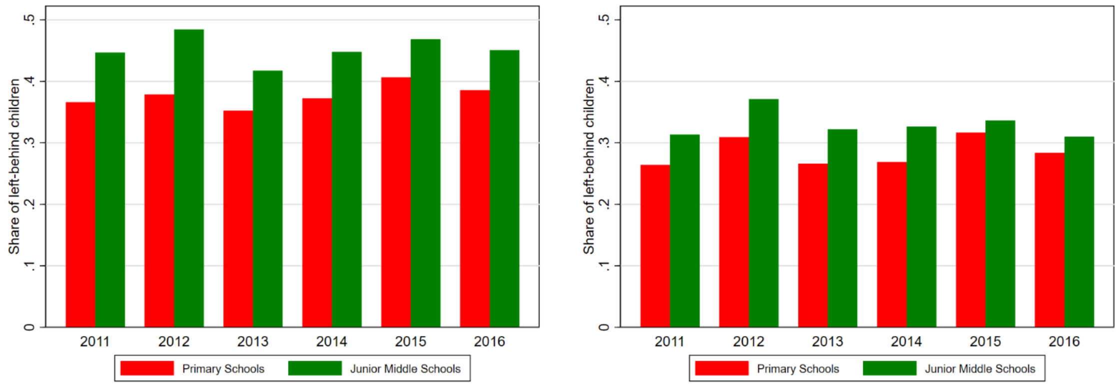
Notes: In China, migrant children without a local *hukou* have to pay *zanzhufei* (an extra fee imposed specifically on them) in order to go to a local school. This figure shows the relationship between the amount of *zanzhufei* and the stringency of *hukou* regulations in migrants' destination cities. Cities are grouped into fifty groups according to the quantile of the *hukou* index. The vertical axis denotes the mean value of the amount of *zanzhufei* and the horizontal axis denotes the mean value of the *hukou* index in each quantile. Data on left-behind children come from the *China Migrants Dynamic Survey (CMDS)*, and data on the *hukou* index come from Zhang et al. (2019).

Figure 4 shows that migrant workers are always more likely to leave middle-school-aged children behind compared to primary-school-aged children. They are also more likely to leave children of all ages behind when they migrate to cities with more stringent *hukou* restrictions. Guangzhou – a popular destination for migrant workers – offers an interesting case study on what happens to migrant children as they transition from primary to middle school age (Table A7). In 2012, about 53% of the children in migrant households studied in primary schools in Guangzhou, but only around 32% of junior middle school aged migrant children stayed in the city. Only 20% took the high school entrance exam.

2.3 The 2014 Migrant Population Control Policy in Mega-Cities

In July 2014, the State Council of China issued "Opinions on Promoting the Hukou System Reform", which urged mega-cities - categorized as those with a population of over five million in the city central district area - to "exercise strict control over the population". Those mega-cities were required to set a population target by 2020,

Figure 4: Share of Left-behind Children by School Age



(a) Highly restrictive cities

(b) Less restrictive cities

Notes: We divide cities into two groups based on the stringency of *hukou* restrictions. Highly restrictive cities are those in which the *hukou* index is above the national mean, and less restrictive cities are those in which the *hukou* index is below the national mean. *Hukou* index measures the stringency of *hukou* regulation and the difficulty for migrants to obtain local *hukou*. Data on left-behind children come from the *China Migrants Dynamic Survey (CMDS)*, and data on the *hukou* index come from Zhang et al. (2019).

and local government performance would be evaluated against that target. Starting in 2014, local governments in mega cities start strongly restricting the inflow of unskilled migrants by imposing even more stringent restrictions on school enrollment for migrant children. The same "Opinion" led to a gradual relaxation of *hukou* restrictions in small and medium-sized cities. We will examine how the leave-behind decisions of migrant parents attached to mega-cities changed after 2014, relative to migrants attached to other cities.

3 Data

3.1 Left-behind Children Data

We use individual-level data on children from the China Migrants Dynamic Survey (CMDS) conducted by the National Health and Welfare Commission. This is the largest nationally representative survey of China's migrant population. The sampling frame consists of migrants who have lived in cities for more than one month but have no local *hukou*. The survey records socioeconomic information of migrant parents and their children's age, gender, education, and residential location. This allows us to identify whether parents leave their children behind in rural areas at different stages of their education.

We combine six waves of the survey from 2011 to 2016 and construct individual-level pooled cross-sectional data for our empirical analysis. We focus on the sample of children whose parents are in cities where we can measure the stringency of *hukou* restrictions. Our baseline sample contains over 171,859 children (47,121 children at junior middle school age and 124,738 children at primary school age) whose parents are rural-urban migrants across 30 provinces.

3.2 Longitudinal Data on Children

We use the Gansu Survey of Children and Families (GSCF) to track long-term socioeconomic outcomes for children. The GSCF is a longitudinal, multi-level study of rural children conducted by the University of Pennsylvania and the Gansu Bureau of Statistics in five waves in 2000, 2004, 2007, 2009 and 2015. The first wave surveyed a representative sample of 2,000 children aged 9–12 across 100 villages in Gansu Province. Subsequent waves track these rural children for 15 more years, which allows us to link their long-term socioeconomic outcomes during adulthood, including educational achievement, earnings, and migration status, with their childhood experience of being left behind by parents or not. We construct individual-level longitudinal panel data by combining GSCF 2000, 2004 and 2015. As we restrict our data to those who appear in the 2015 wave, our longitudinal panel data has 1414 individuals. The survey attrition rate is not significantly different between those who experienced parental absence during school age and those who did not.

3.3 Hukou Restrictions Data

We use the *hukou* index constructed by Zhang et al. (2019) to measure the stringency of *hukou* regulations across Chinese cities. The main mechanisms by which migrants qualify for an urban *hukou* include tax payment and investment, home purchase, and employment.[5] The requirements associated with each mechanism differ by cities, and the composite *hukou* index measures the overall difficulty for adult migrants to obtain a local *hukou*. Because China experienced significant changes in the *hukou* policy in 2014,[6] Zhang et al. (2019) construct city-level *hukou* index specific for the periods of 2000–2013 and 2014–2016.

3.4 Data to Construct Instrumental Variables

Estimating the consequences associated with leaving children behind requires us to develop a few instruments for parents' decisions to migrate leaving children behind. One of the instruments uses a labor demand shock in nearby cities due to international trade, which is a pull factor for rural migrant workers. The raw data used to calculate world import demand are drawn from the International Trade Statistics Database of UN Comtrade. Second, we leverage rainfall variation during the planting season in rural areas as a push factor, with data from the China Meteorological Data Service Center. Rainfall is interacted with each rural area's historical ties to migration destinations, which is a function of visitors from those destinations in each rural area. We construct this using the China Population 1982. Appendix Table A1 reports summary statistics of the key variables used in the analysis.

4 Results on Leaving Children Behind

4.1 A Regression Discontinuity Design Based on School Enrollment Age

Given the increased difficulty migrant parents face to enroll their children in urban junior middle schools, we test whether the propensity to leave children behind changes at the age cutoff for middle school entry. We show the regression discontinuity (RD)

[5] We ignore the family reunion channel in our index construction, because only a very small fraction of immigrants can obtain local *hukou* through this channel.

[6] China experienced two rounds of *hukou* reforms in the past two decades. First, in the early 2000s, many provinces abolished the quota system for rural to urban *hukou* transition. The state abolished the grain and oil permit system, thus separating the food supply from *hukou* registration. Although abolishing the quota system lowered the barrier for *hukou* transition, it was still very hard for internal migrants to obtain a local *hukou* in most Chinese cities during that period. Second, in 2014, following the issuance of "Policies on the Reform of the Household Registration System," small and medium-sized cities loosened restrictions while large cities strengthened them.

result both graphically and using the following regression specification:

$$\begin{aligned} Left\ behind_{ijt} = &\psi_0 + \psi_1 SchoolAged_{it} \times High\ Hukou_{jt} + \psi_2 SchoolAged_{it} + \\ &\psi_3 T_j \times SchoolAged_{it} + \psi_4 T_j + \xi_{jt} + \eta_n + v_{ijt} \end{aligned} \tag{1}$$

where $Left\ behind_{ijt}$ is an indicator for whether child i (whose parents work in city j and do not have a local *hukou* in their place of residence) are left behind in a rural area in year t.[7] $SchoolAged_{it}$ is an indicator for whether child i is above the enrollment age for junior middle school, based on their exact date of birth relative to the September 1 school entry date.[8] $High\ Hukou_{jt}$ is a binary variable that equals one if the stringency level of *hukou* restrictions in city j and year t is above the average city level. The running variable T_j is the number of years between school enrollment age and children's age. Our primary variable of interest is the interaction between $SchoolAged_{it}$ and $High\ Hukou_{jt}$, which examines whether there is any differential discontinuous shift in the probability of leaving children behind at the school enrollment age ($T_j = 0$) in cities with more restrictive *hukou* policies. We combine CMDS 2011-2016 to create an individual-level pooled cross-sectional dataset to estimate equation (1).

We estimate equation 1 separately for male and female children to examine whether migrant parents' decisions vary by the gender of their child. Imbens and Lemieux (2008) and Gelman and Imbens (2019) suggest that a local linear regression using samples near the RD cutoff is likely to yield the most robust estimates. We use a local linear control function for the running variable T_j, and select two years as the bandwidth in our baseline specification. We conduct robustness checks with alternative bandwidths and control functions for T_j.

We add city-by-year fixed effects ξ_{jt} to control for city-by-year characteristics such as industrial structure and economic development plans of local government that may be correlated with the city's *hukou* policies . We control birth cohort fixed effects η_n to account for any changes in other policies (e.g. the One Child Policy) pertaining to

[7] We exclude rural-urban migrants who migrated from rural to urban areas within the same prefecture-level region. This is because a rural and an urban area located within the same prefecture are close, and can be within commutable distance.

[8] Our empirical identification strategy is a fuzzy RD design, as some migrant workers may send their children to a junior middle school later than the compulsory enrollment age.

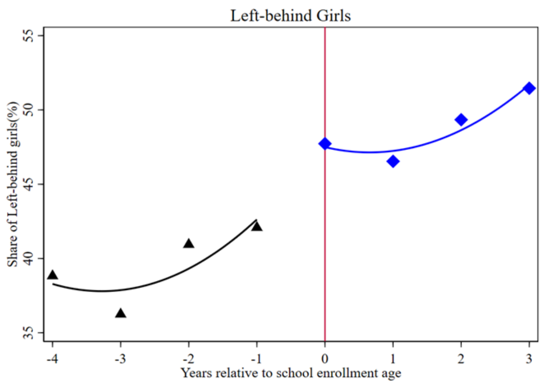
child outcomes. Table A8 examines whether other variables change systematically at the RD cutoff. We do not see any discontinuities in the fraction of migrants who get a local urban *hukou*, parents' migration decisions, or incomes.

A potential concern with the RD strategy is that parents change destinations or try harder to obtain a local *hukou* when their children reach middle school enrollment age. Table A8 directly tests for this and finds that parents' migration decisions or their probability of getting a local *hukou* do not meaningfully change at that school-age cutoff. A remaining concern is that perhaps families disappear from our dataset entirely due to changes in their migration choices. To explore, we follow Cattaneo et al. (2020) and perform a data-driven manipulation test, in which we compare the density of observations around the RD cutoff. As reported in Table A9, we find no discontinuity in the sample distribution at the school-age cutoff for either male or female children. This mitigates concerns about "sorting" (e.g. changing *hukou* location) based on their child's school entry date.

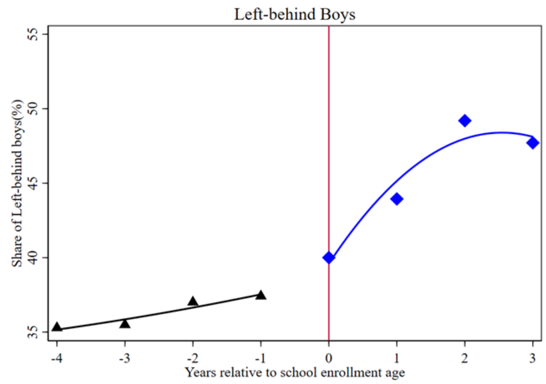
4.2 Graphical Analysis of the Regression Discontinuity

Figure 5 graphically represents shifts in the fraction of left-behind children at the age cutoff for middle school enrollment . Reflecting our triple difference research design, we show separate graphs for sons and daughters, and for cities where migrant parents face more or less stringent *hukou* restrictions. There is a sharp increase in the share of left-behind girls just at the school enrollment age if their parents are in highly *hukou*-restricted cities (Figure 5a), whereas we do not observe any discontinuous changes at the enrollment age for boys in those highly *hukou*-restricted cities (Figure 5b). We also do not observe any discontinuity for either girls or boys in less *hukou*-restricted cities (Figures 5c and 5d). In addition, irrespective of child gender, the fraction of children that are left behind is much lower in less restricted cities than it is in highly restricted cities. Migrant parents appear to leave their daughters rather than their sons in their rural hometown in response to strict *hukou* restrictions, whereas there is no obvious gender bias for parents in cities with relaxed *hukou* policies .

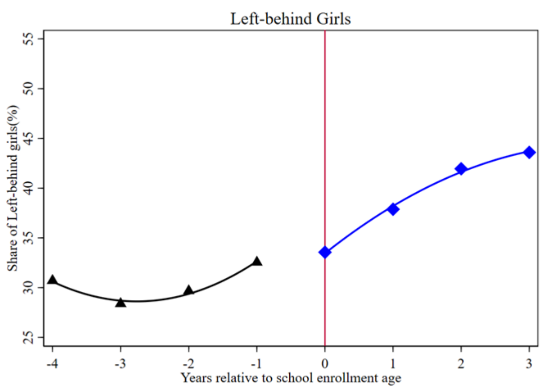
Figure 5: School Enrollment and Left-behind Children



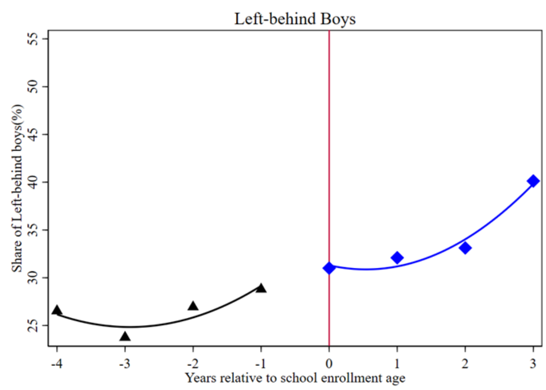
(a) Girls in *highly* restrictive cities



(b) Boys in *highly* restrictive cities



(c) Girls in *less* restrictive cities



(d) Boys in *less* restrictive cities

Notes: The vertical axis shows the share of children left behind in villages, for girls and boys, repectively. The horizontal axis shows the number of years relative to the junior middle school enrollment age. We divide cities into two groups based on the stringency of *hukou* restrictions. Highly restrictive cities are those in which the *hukou* index is above the national mean, and less restrictive cities are those in which the *hukou* index is below the national mean. Hukou index measures the stringency of *hukou regulation* and the difficulty for migrants to obtain local *hukou*. Data on left-behind children come from the *China Migrants Dynamic Survey (CMDS)*, and data on the *hukou* index come from Zhang et al. (2019).

4.3 Regression Analysis

We estimate equation 1 to statistically examine the discontinuity described above. The dependent variable in Table 1 is a binary indicator for the decision to leave the child behind, and our independent variable of interest is the interaction between the indicator for the child reaching junior-middle-school enrollment age and an indicator for parents in cities with above-average stringency of *hukou*-restrictions. Our baseline specifications use two years as the bandwidth around the age cutoff and employ a local linear control function for the running variable. We perform the analysis separately for daughters (columns 1-4) and sons (columns 5-8).

We control for city-by-year fixed effects in columns 1, 2, 3, 4. To absorb any differences in attitudes towards boys' versus girls' education between migrants from different areas, columns 5, 6, 7, 8 add a triple interaction between city-, year- and *hukou* province- fixed effects. Columns 3, 4, 7, 8 add birth cohort fixed effects. All columns control for household socioeconomic characteristics.

Across all the specifications for daughters (columns 1, 3, 5, 7), the interaction of the above-enrollment-age indicator and the high-*hukou*-restriction indicator is statistically significant, and the coefficient implies that a girl becomes 3.2-3.5 percentage points more likely to be left behind exactly when she reaches the legal enrollment age for junior middle school and her parents work in a city with restrictive *hukou* policy.[9] 34% of girls in migrant households in China are left behind in rural areas, so the discontinuous jump at that age-cutoff represents a 10% increase at the mean. The coefficient on the above-enrollment-age dummy is close to zero, which suggests that the discontinuity does not exist for parents who migrated to cities with relatively relaxed *hukou* policies.

Across all specifications for sons (columns 2, 4, 6, 8), both the above-enrollment-age indicator and its interaction with the high-*hukou*-restriction indicator are statistically indistinguishable from zero. In addition, the coefficients on the interaction term of interest is statistically larger for the sample of daughters compared to the sample of sons. Table A11 combines the two samples and conducts triple difference regressions to formally demonstrate that the school-age discontinuity in restrictive *hukou* cities

[9] Table A10 shows that the results remain similar under RD design variations in which we extend the bandwidth or use a quadratic control function for the running variable.

is statistically larger for girls.

In contrast to daughters, the elevated entry fees for middle school does not appear to deter migrant parents from keeping their sons with them in the city, regardless of how stringent the *hukou* restrictions are. China's *hukou* policies are not formally gender-specific by design, but when that schooling expense is imposed on parents, they seem more willing to sacrifice time with their daughters. This is reminiscent of Dahl and Moretti (2008)'s findings that American parents seem to prefer spending time with sons. Some pre-existing underlying son preference in China appears to be interacting with mobility restrictions to produce gender-unequal outcomes.

Table 2 shows that of the children left behind in rural areas by migrant parents, the majority are left behind without either parent present. These cases account for 24% of the 34% of rural children that are left behind. Furthermore, the discontinuous jump in parents' propensity to leave daughters behind at middle-school-age most often leads to those additional daughters being left behind in rural areas without either parent present. This is relevant because the emotional toll and developmental burden on children are likely larger when both parents are absent (Zhang et al., 2014). Other descriptive data from China shows that in such cases, grandparents are asked to take care of children left behind in rural areas.

Table 1: School Enrollment Age and left-behind Children

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Indicator for leaving the child in rural hometown							
	Female	Male	Female	Male	Female	Male	Female	Male
School-aged × Highly restricted cities (=1) (ψ_1)	0.0324**	0.00331	0.0330**	0.00444	0.0349**	0.00871	0.0354**	0.00984
	(0.0145)	(0.0150)	(0.0144)	(0.0148)	(0.0145)	(0.0170)	(0.0144)	(0.0167)
School-aged (ψ_2)	-0.00451	0.000905	-0.00545	0.00125	-0.00375	0.000643	-0.00644	0.000597
	(0.0158)	(0.0136)	(0.0159)	(0.0134)	(0.0176)	(0.0153)	(0.0178)	(0.0152)
P-value of $\psi_1 + \psi_2$	0.0341	0.679	0.0397	0.576	0.0149	0.400	0.0271	0.360
Coeff diff p-value	0.00		0.00		0.00		0.00	
Observations	31,071	40,854	31,071	40,854	31,071	40,854	31,071	40,854
Adjusted R-squared	0.172	0.146	0.173	0.147	0.206	0.184	0.207	0.184
Mean of Dep. Var.	0.35	0.34	0.35	0.34	0.35	0.34	0.35	0.34
Household Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	Yes	Yes	No	No	No	No
City FE×Year FE×*Hukou* Province FE	No	No	No	No	Yes	Yes	Yes	Yes
Cohort FE	No	No	Yes	Yes	No	No	Yes	Yes
Age Bandwidth	2	2	2	2	2	2	2	2
Control function for the running variable	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear

Notes: This table shows the results of estimating equation 1. The bandwidth is two years. We use a RD sample of children who are two years older or younger than the enrollment age of junior middle school. "Coeff diff p-value" reports the p-value of a test of equality of (ψ_1) between the female and male, using the Fisher's permutation test. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. We use a local linear control function for the running variable. Robust standard errors clustered at the city level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: One Parent Versus Both Parents Are Separated from Children

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Indicator for leaving the child in rural hometown							
	Female	Male	Female	Male	Female	Male	Female	Male
Panel A: Dependent Variable: Indicator for leaving the child behind without both parents								
School-aged × Highly restricted cities (=1) (ψ_1)	0.0202*	0.00615	0.0208*	0.00726	0.0230**	0.00912	0.0236**	0.0102
	(0.0118)	(0.0124)	(0.0117)	(0.0121)	(0.0107)	(0.0143)	(0.0106)	(0.0138)
School-aged (ψ_2)	-0.00903	-0.00126	-0.0145	-0.00500	-0.00770	-0.00151	-0.0137	-0.00559
	(0.0133)	(0.0129)	(0.0132)	(0.0129)	(0.0137)	(0.0143)	(0.0136)	(0.0142)
Observations	31,071	40,854	31,071	40,854	31,071	40,854	31,071	40,854
Adjusted R-squared	0.130	0.142	0.131	0.142	0.188	0.174	0.189	0.175
Mean of Dep. Var.	0.24	0.23	0.24	0.23	0.24	0.23	0.24	0.23
Panel B: Dependent Variable: Indicator for leaving the child behind with one parent								
School-aged × Highly restricted cities (=1) (ψ_1)	0.0117	-0.00284	0.0117	-0.00282	0.0119	-0.000407	0.0118	-0.000347
	(0.00733)	(0.00595)	(0.00747)	(0.00589)	(0.00778)	(0.00643)	(0.00793)	(0.00634)
School-aged (ψ_2)	0.00683	0.00216	0.0109	0.00624	0.00394	0.00216	0.00725	0.00619
	(0.00831)	(0.00749)	(0.00847)	(0.00744)	(0.00881)	(0.00705)	(0.00915)	(0.00696)
Observations	31,071	40,854	31,071	40,854	31,071	40,854	31,071	40,854
Adjusted R-squared	0.207	0.179	0.208	0.180	0.252	0.225	0.253	0.226
Mean of Dep. Var.	0.10	0.11	0.10	0.11	0.10	0.11	0.10	0.11
Household Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	Yes	Yes	No	No	No	No
City FE×Year FE×*Hukou* Province FE	No	No	No	No	Yes	Yes	Yes	Yes
Cohort FE	No	No	Yes	Yes	No	No	Yes	Yes
Age Bandwidth	2	2	2	2	2	2	2	2
Control function for the running variable	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear

Notes: The bandwidth is two years. We use a RD sample of children who are two years older or younger than the enrollment age of junior middle school. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. We use a local linear control function for the running variable. Robust standard errors clustered at the city level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.4 Threats to Identification

Given son preference in China and the availability of sex selection technology, there is a plausible concern that child gender may itself reflect parental choices. Existing evidence suggests that sex selection is more common at higher birth orders, but observed gender ratio of first-born children in China match biological expectations (Almond et al., 2019). We therefore re-run our regressions in Table A12 limiting the sample to first-born children only. The empirical patterns remain very similar, where daughters of parents in *hukou*-restrictive cities become 3.7-4.2 percentage points more likely to be left behind when they cross the age threshold for middle-school entry.

Some features of China's One Child Policy (OCP) may pose additional threats to causal inference from our regression discontinuity design (Qian, 2018; Rosenzweig and Zhang, 2009; Gao et al., 2022). First, in some provinces, the local government allows rural parents who have a second child only if their first-born is a girl. As a result, the gender of the child in our RD analysis may be systematically correlated with family size. In Table A13, we therefore re-run the RD regression controlling for the number of children (Panel A), and fixed effects for family size (Panel B). Our results remain robust, even when comparing between households with the exact same number of children.

Second, the penalties for violating OCP guidelines vary by province and by ethnicity.[10] Parents' gender preferences can also vary by province and ethnicity, which may create some accidental correlation where we mis-attribute OCP effects to migration restrictions. In Table A14, we control for triple interactions between parents' ethnicity fixed effects, cohort fixed effects, and the parents' *hukou*-province fixed effects (which governs the OCP guidelines they are subjected to) to account for any potential confounding effect of the OCP. Our RD results do not change after including these controls.

[10]For example, the OCP restricted fertility for Han people between 1979 and 2016, but not for ethnic minorities. The punishment for violating the OCP (such as financial penalties) varied across provinces.

4.5 Another RD Design Based on 2014 Mega-city Migrant Population Control Policy

Our use of cross-city variation in the stringency of *hukou* restrictions introduces a concern that unobserved educational preferences drives the choice of city the parents migrate to. We therefore use the 2014 "migrant population control policy" imposed on mega cities to construct a different RD research design to again test for gender biases in migrant parents' decisions on whether to leave their children behind. This new policy forced local governments in mega-cities to impose new restrictions on migrants' access to local public services. Since "mega-cities" have a precise definition (population exceeding five million in the city central district), we construct the following RD specification based on that population threshold:

$$\begin{aligned} Left\ behind_{ijt} = & \alpha_0 + \alpha_1 School\ Age_{it} \times I(Pop > 5\ million)_j \times I(t > 2014) + \\ & \alpha_2 School\ Age_{it} \times I(Pop > 5\ million)_j + \alpha_3 School\ Age_{it} \\ & \times I(t > 2014) + \alpha_4 School\ Age_{it} + \xi_{jt} + \eta_n + v_{ijt} \end{aligned} \tag{2}$$

where $School\ Age_{it}$ is an indicator for children who have reached middle-school enrollment age by year t, $I\left(Pop > 5\ million\right)_j$ is an indicator for the mega-cities subjected to the new policy because their central district population at baseline exceeded 5 million, and $I\left(t > 2014\right)$ is an indicator for the post-treatment period. The running variable in this RD design is the city-specific difference between baseline city population and 5 million, which is absorbed by city-by-year fixed effects–ξ_{jt}. We restrict the sample to parents who made their migration destination choices before 2014, to mitigate any reverse causality concerns about parents choosing destinations based on concerns about children's access to urban schools.

Columns 1 and 3 of Table 3 show that for female children, the RD variable of interest—the triple interaction between having reached the junior middle school enrollment age; the indicator for cities with above-5-million population; and the indicator for post-2014—is positive and significantly different from zero. In response to the new policy, parents who had migrated to mega-cities prior to 2014 become 7 percentage points more likely to leave daughters behind. The second row shows that parents were not exhibiting that behavior before the policy went into effect. Columns 3-4 show that there is no such effect for boys in migrant households. All these coefficients jointly imply that new migration restrictions that increase the cost of raising children in the city pushes parents into discriminating against their daughters.

A potential concern with this second RD design is that parents anticipate the 2014 population control policy, and those with middle-school-aged kids choose to relocate from mega-cities. Table A15 tests this directly, and the RD (triple interaction) condition does not predict relocation. Table A16 restricts the sample of migrant parents further to those who made destination choices before 2013 or 2012, and our results remain robust in these sub-samples.

Table 3: An Alternative RD Design based on Population Controls in Mega Cities

	(1)	(2)	(3)	(4)
Dependent Variable: Indicator for leaving the child in rural hometown				
	Female	Male	Female	Male
Above enrollment age ×I(Population>5 million) × I(Year>2014)	0.0700***	-0.0429	0.0772**	-0.0314
	(0.0220)	(0.0363)	(0.0306)	(0.0267)
Above enrollment age ×I(Population>5 million)	-0.00355	0.0186	-0.00946	0.00909
	(0.0222)	(0.0139)	(0.0197)	(0.0153)
Above enrollment age (ψ_2) × I(Year>2014)	-0.0495**	0.0342	-0.0491	0.0434
	(0.0214)	(0.0262)	(0.0291)	(0.0277)
Above enrollment age (ψ_2)	0.0314*	-0.0240	0.0453**	-0.0200
	(0.0173)	(0.0166)	(0.0172)	(0.0186)
Coeff diff p-value	0.000		0.000	
Observations	10,296	13,812	10,296	13,812
Adjusted R-squared	0.163	0.137	0.192	0.169
Household Control	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	No	No
City FE×Year FE×*Hukou* Province FE	No	No	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Age Bandwidth	2	2	2	2
City Size Bandwidth	3	3	3	3

Notes: The age bandwidth is two years. We use a RD sample of children who are two years older or younger than the enrollment age of junior middle school. "Coeff diff p-value" reports the p-value of a test of equality of "Above enrollment age ×I(Population>5 million) ×I(Year>2014)" between the female and male, using the Fisher's permutation test. The city size bandwidth is 3 million, and thus we only include cities with population between 2 and 8 million in the city central district area . Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. Robust standard errors clustered at the city level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5 Remittance Behavior

Leaving children behind in rural areas reduces the cost of raising children because parents can avoid paying extra urban school fees. Therefore, migrant parents could afford to compensate daughters for separating from them by sending remittances back to the rural area. Both parental time and money are useful for child development, so it's possible that this is on net beneficial for daughters. Table 4 examines the patterns of remittances sent back by migrant parents as a function of child gender. Remittance sent back is actually 9% *lower* when a daughter is left behind compared to a son being left behind. In panel C, we see that this gender difference gets even larger when the child reaches junior-middle-school age. In this sample, remittances are 13-16% lower for left-behind girls. Given the usual identification concerns about sex selection, Appendix Table A17 restricts this analysis sample to first-born children, where gender-ratio-at-birth follows biological norms (Almond et al., 2019). Estimated effects are even larger: middle-school-aged first-born daughters receive 15-17% less remittances from migrant parents than first-born sons.

In summary, there is no evidence that daughters who (our previous analysis shows) are more likely to be left behind at that age are financially compensated by parents. Daughters receive less time and less money from their parents.

6 Long-term Effects of Leaving Children Behind

We now use longitudinal data to study the longer term consequences of being left-behind as a child on socio-economic outcomes in adulthood, observed 15 years later. We estimate the following specification using data from the 2000, 2004, and 2015 rounds of the Gansu Survey of Children and Families (GSCF), which track a group of children born in rural Gansu over a long period:

$$Y_{ict} = \beta_0 + \beta_1 Left\ behind_{ict} + \xi_m + \eta_t + \varepsilon_{it} \tag{3}$$

We use information on the parents' location to identify children who were either living with their parents, or were left behind when they were middle-school-age in 2000 or

Table 4: Remittance sent to rural children by gender

	(1)	(2)	(3)	(4)
	Dependent variable: IHS of the Amount of Remittance			
Panel A: Full Sample				
Female	-0.0872***	-0.0890***	-0.0928***	-0.0956***
	(0.0332)	(0.0332)	(0.0342)	(0.0341)
Observations	39,556	39,556	39,556	39,556
Adjusted R-squared	0.0778	0.0785	0.124	0.125
Panel B: Primary School Age				
Female	-0.0980*	-0.0971*	-0.0952*	-0.0925*
	(0.0530)	(0.0530)	(0.0558)	(0.0559)
Observations	14,460	14,460	14,460	14,460
Adjusted R-squared	0.0810	0.0814	0.133	0.133
Panel C: Junior Middle School Age				
Female	-0.134**	-0.135**	-0.165**	-0.164**
	(0.0653)	(0.0642)	(0.0702)	(0.0689)
Observations	8,018	8,018	8,018	8,018
Adjusted R-squared	0.0818	0.0816	0.113	0.112
Household Control	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	No	No
City FE×Year FE×*Hukou* Province FE	No	No	Yes	Yes
Cohort FE	No	Yes	No	Yes

Notes: The Inverse Hyperbolic Sine (IHS) transformation is applied to the amount of remittance.Panel A shows results for all children aged below 16, and panels B and C, respectively, show results for children at primary school age and junior middle school age. We use the CMDS 2011 and 2012 to perform estimation as only the two waves of CMDS contain information about remittance. Robust standard errors clustered at the city level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

2004.[11] Socio-economic outcomes Y_{ict} are measured in 2015 for individual i born in a rural area in prefecture c in year t.[12] In our main specifications, $Left\ behind_{ict}$ is an indicator for whether child i was separated from at least one parent for more than six months in a survey year (2000 or 2004) during junior middle school age. We control for residential township fixed effects ξ_m, and birth cohorts fixed effects, η_n.

Note an important difference in the structure of this data relative to datasets we used in our earlier analysis in section 4: in this panel dataset, left-behind children are those who have a parent who migrated but the child continues to live in a rural area, while parents of the "control group" are non-migrants. 17% of the children in our Gansu sample were separated from one or both parents during childhood. Each parent's decision about whether to migrate is an endogenous choice, so we need an instrument for the parents' migration decision to isolate the causal effect of leaving children behind.

6.1 Instrument #1: Import Demand Shocks in Nearby Cities

Since the growth in China that induced this large-scale rural-urban migration was export-led, we can use global import demand shocks for the products/industries that each city specializes in as sources of exogenous variation that drive migration choices from nearby rural regions of Gansu.[13] Using UN Comtrade data on imports[14], we create an index called WID_{ct}, which measures each rural region's exposure to a world

[11]Because the initial wave of GSCF in 2000 surveyed children aged 9–12, and the school age for junior middle school is 12-15 (if born before Sept 1) or 13-16 (born after Sept 1), the 2000 and 2004 survey waves offer us the opportunity to observe children separated from parents during middle school age.

[12]All children in our sample hold a rural *hukou* in the prefecture of birth in 2000 and 2004. In China, a prefecture region includes both rural and urban areas. The GSCF covers children in rural areas in 11 prefectures.

[13]Gansu is a large geographically spread province and the survey districts abut a variety of cities that experienced import demand shocks: Xi'an, Chengdu, Xining. The *hukou* index in those potential migration destinations ranges from 0.051 to 0.304, whereas the mean and SD of the *hukou* index across all Chinese cities are 0.171 and 0.097. The range of exposure to world import demand shocks exceeds four standard deviations.

[14]The International Trade Statistics Database of UN Comtrade contains detailed information on each world trade flow, including the corresponding importer, exporter, the Harmonized System (HS) 6-digit code, and total values. We calculate total imports for each HS 6-digit product at the world level and concord the HS level data to International Standard Industrial Classification industries.

import demand shock in each year. The import demand shock experienced by each city is defined as the 2-year increase in import demand for industry k weighted by the importance of that industry to destination city d, as measured by that city's pre-period (1997) export share of that industry ($\frac{EX_{k,d}}{\sum_j EX_{k,j}}$) prior to China's accession to the World Trade Organisation. Every city experiences these demand shocks, so each rural region's exposure is determined by their proximity to every "potential" migration destination. We therefore weight the city-specific demand shocks by the inverse of the distance from the migrant's birth location c to every urban destination d, to create the index for rural region c:

$$WID_{ct} = \sum_d \left(\frac{1}{dist_{dc}}\right)\left(\sum_k World\ IM_{k,t-2,\ \ t} \times \frac{EX_{k,d}}{\sum_j EX_{k,j}}\right) \tag{4}$$

This is akin to "shift-share" instruments common in the economics literature. We assign non-zero weights only to potential destination cities that are located within a 400 km radius of birthplace c. The exact instrument we use in our regressions is the interaction between WID_{ct} and restrictiveness of *hukou* regulations in nearby cities, because we are trying to extract the migrant's pull to destinations where they cannot easily take their children. The specification of the first-stage estimation is:

$$\begin{aligned} Left\ behind_{icn,t} =& \gamma_0 + \gamma_1 WID_{ct} \times Des\_High\ Hukou\ _c + \gamma_2 WID_{ct} + \xi_c \\ &+ \eta_{n,\ t} \times Female + \varepsilon_{icn,t} \end{aligned} \tag{5}$$

$Des\_High\ Hukou\ _c$ is an indicator for whether migrants from birthplace c would face stringent *hukou* restrictions in cities near location c. We first compute the inverse distance-weighted sum of the *hukou* index across potential destination cities, $\sum_d \left(\frac{1}{dist_{dc}} Hukou\ Index_d\right)$, and consistent with our approach in section 4, the indicator $Des\_High\ Hukou\ _c$ turns on if $\sum_d \left(\frac{1}{dist_{dc}} Hukou\ Index_d\right)$ is above the average level of all cities.

We directly control for WID_{ct} (and $Des\_High\ Hukou\ _c$ is absorbed by the location fixed effects ξ_c) in the first and second stages of this 2SLS strategy, so only the interaction between WID shocks and *hukou* restrictions acts as the excluded instrument. The exclusion restriction of this instrument is violated if positive import demand shocks in nearby cities affect children growing up in rural Gansu through mechanisms other than being left behind by migrant parents. That's actually a very plausible concern: increased world import demand likely raises wages for migrant parents (which could benefit children in other ways), and if the shock persists, it could create future economic opportunities for the children as they enter adulthood, and it could also thereby raise their perceived returns to education. All of that should *improve* child education and economic outcomes, while we estimate the opposite, as previewed in the introduction: Gansu children are worse off in multiple dimensions when their parents migrate and leave them behind. Violations of the exclusion restriction therefore lead to an *underestimation* of the detrimental effects of leaving children behind. Our estimates, if anything, will be *conservative* in magnitude.

6.2 Instrument #2: Rainfall and Historical Migration Ties

Our first instrument is created based on shift-share "pull" shocks in cities that attract rural people to migrate. We next leverage "push" factors in places of origin. In particular, our second instrument is the interaction of rainfall in original location interacted with historical migration ties. The specification of the first-stage estimation is:

$$\begin{aligned} Left\ behind_{icn,t} =& \gamma_0 + \gamma_1 Rain_{ct} \times \ Mig\ Tier_c + \gamma_2 Rain_{ct} + \xi_c \\ &+ \eta_{n,\ t} \times Female + \varepsilon_{icn,t} \end{aligned} \tag{6}$$

where $Rain_{ct}$ is the rainfall in the planting season in birth location c and year t. Decreased rainfall in the planting season can negatively affect agricultural productivity. A positive income shock from rainfall can either hold migrants back in the rural area, or it could relax liquidity constraints and permit more migration (Bazzi, 2017).

Like Imbert et al. (2022), we combine this rainfall shock with those rural areas' pre-existing connection to cities in order to predict migration propensity. Internal migration was prohibited before 1984, so any migration was mainly driven by government programs like the *Sent Down Youth* campaign, which was a reverse urban-to-rural flow that created idiosyncratic historical variation in each rural region's connection to cities from which the youth had visited. We use the Population Census 1982 to calculate the share of in-migrants to rural birth location c to measure such migration network ties. Rural areas that had hosted in-migrants from a large city may have retained better personal connections and knowledge about that city, which in turn increases the desirability or salience of that city as a possible migration destination (Kinnan et al., 2018).

We employ the two instruments discussed above independently as they represent very different sources of variation (driven by "pull" demand shocks in potential destination cities versus "push" weather shocks in places of origin). In Table A18, we show the strength of the first-stage relationships between our different instruments and our (endogenous) independent variable of interest.

6.3 Results on Long-term Socioeconomic Outcomes

Table 5 reports the effects of being left-behind by a migrant parent on the educational attainment of children (the empirical estimate of equation 3). We control for birth location fixed effects and cohort fixed effects, and (sometimes) for household characteristics like whether a grandparent is alive and whether a grandparent resides in the same village. Appendix Table A18 shows the first stage of these instrumental variables estimates (equation 5), and Appendix Table A19 shows the reduced form results of regressing human capital achievements directly on the World Import Demand shocks instrument defined by equation 4.

All results indicate that parental absence during childhood has significant negative effects on long-term educational outcomes. Leaving children in poor rural areas during junior middle school age reduces schooling attainment by three years (Table 5). This is a very large effect that represents 0.85 standard deviations of the dependent variable. Columns 3-4 further show that the years of schooling are 28-29 percentage points lower for those who experienced parental absence during school age than for those who did not.

We next restrict our sample to the subset of children who took high school entrance exams. Separation from parents during junior middle school age reduces their probability of passing high school entrance exams by as much as 41-45 percentage points (columns 5 and 6). This result is especially striking because anecdotally, a reason migrants often provide for sending their middle-school-aged-child back is so that the child can prepare for the high-school entrance exam, for which the curriculum

Table 5: The Effects of Leaving Children Behind on Education Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Years of Schooling		IHS of Years of Schooling		Pass High School Entrance Exams (=1)	
Indicator for leaving the child behind	-2.863***	-3.005***	-0.277***	-0.290**	-0.411*	-0.446*
	(0.561)	(0.697)	(0.0769)	(0.0980)	(0.194)	(0.232)
F stat	50.97	43.33	50.97	43.33	37.28	36.29
Observations	1,335	1,335	1,335	1,335	946	946
Mean of Dep. Var.	11.37	11.37	3.07	3.07	0.67	0.67
SD of Dep. Var.	3.510	3.510	0.381	0.381	0.469	0.469
Household Controls	No	Yes	No	Yes	No	Yes
Township FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Instrumental variables specification using the interaction of World Import Demand (WID) and *hukou* restrictions. We drop observations with missing values in the dependent variables. Household controls include an indicator for whether a grandparent was alive and an indicator for whether a grandparent was living in the same place. Like Khanna et al. (2020), we control for import tariffs which may affect firm productivity. The Inverse Hyperbolic Sine (IHS) transformation is applied to years of schooling (columns 3 and 4). We restrict our sample to those who had taken high school entrance exams in columns 5 and 6. Robust standard errors clustered at the prefecture of birth level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

varies by provinces.

Table 6 further shows that being left behind also significantly negatively affects later-life health and socioeconomic outcomes. Parental absence during school age increases the probability that the child appears in the bottom quartile of the income distribution of Gansu in 2015 by 35-36 percentage points (columns 1 and 2).[15]

Columns 3-6 report effects on two measures of mental health available in the GSCF 2015 survey round. Separation from parents significantly increases the risk of "being distracted" later in life.[16] It also undermines the individual's ability to deal with stress in adulthood (columns 5-6).[17] Columns 7-8 show that left-behind children also suffer from worse physical health: they are more likely to be obese later in life.

Table A20 shows alternate estimates of the long-term consequences on education using the other (rainfall × historical migration ties) instrument (equation 6). The

[15]We use data from China Family Panel Survey to construct the 2015 income distribution for people who were born in Gansu Province. Our dependent variable - "low income group" include those in the bottom quartile and those who report no income.

[16]Based on a 5-point scale survey question: "Are you more easily distracted?" (1=strongly disagree; 2= disagree; 3= neither agree nor disagree; 4=agree; 5=strongly agree)

[17]Also based on a 5-point scale survey question: "Are you able to cope with stress?" (1=strongly disagree; 2= disagree; 3= neither agree nor disagree; 4=agree; 5=strongly agree).

Table 6: The Effects of Leaving Children Behind on Health and Labor Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low Income Group (=1)		Level of Distraction		Capability of Coping with Stress		Obesity (BMI>30)	
Indicator for leaving the	0.346*	0.358*	1.042***	1.046***	-0.803**	-0.791**	0.109**	0.108**
child behind	(0.184)	(0.177)	(0.310)	(0.318)	(0.316)	(0.310)	(0.0345)	(0.0358)
F stat	47.55	37.70	92.59	96.55	110.2	117.4	47.51	37.67
Observations	1,379	1,379	904	904	911	911	1,379	1,379
Mean of Dep. Var.	0.493	0.493	2.77	2.77	3.59	3.59	0.026	0.026
SD of Dep. Var.	0.500	0.500	0.844	0.844	0.735	0.735	0.160	0.160
Household Controls	No	Yes	No	Yes	No	Yes	No	Yes
Township FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Instrumental variables specification using the interaction of World Import Demand (WID) and *hukou* restrictions. We drop observations with missing values in the dependent variables. Household controls include an indicator for whether a grandparent was alive and an indicator for whether a grandparent was living in the same place. Like Khanna et al. (2020), we control for import tariffs which may affect firm productivity. We divide the children in our sample into two groups based on their income in 2015; the low-income group includes those whose income is below the bottom quartile of 2015 income distribution for people who were born in Gansu and those who do not have any income (columns 1 and 2). We use the CFPS data to look at the 2015 income distribution for people who were born in Gansu. In GSCF 2015, there is a survey question: Are you more easily distracted (1=strongly disagree; 2= disagree; 3= neither agree nor disagree; 4=agree; 5=strongly agree). Based on this question we define the level of distraction (columns 3 and 4): =1 if the answer is strongly disagree;...; =5 if the answer is strongly agree. There is another survey question in GSCF: Are you able to cope with stress (1=strongly disagree; 2= disagree; 3= neither agree nor disagree; 4=agree; 5=strongly agree). Based on this question we define the capability of coping with stress (columns 5 and 6): =1 if the answer is strongly disagree;..; =5 if the answer is strongly agree. Robust standard errors clustered at the prefecture of birth level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

coefficient estimates are slightly larger in magnitude and show a very similar empirical pattern: leaving children behind has a significant negative effect on their educational achievement. In Table A21, we change the RHS measure in equation 3 to "the amount of time that parents are away from children when they are school-aged", and the results remain very similar.

6.4 We Under-estimate the Costs of Leaving Children Behind

The first part of our paper analyzing parents' decisions to leave children behind uses different datasets and sources of variation than the second part analyzing long-term consequences. This leads to a possibility that the costs of family separation estimated using longitudinal data do not apply to the daughters who parents choose to leave behind, as identified through our RD analysis. This sub-section considers the possible sources of discrepancies to identify whether we are over- or under-estimating the costs imposed on children who are left behind.

In section 4, we focus on migrant parents' choice of whether to keep their children with them in the city, or send them back to the rural origin. In contrast, our longitudinal data compares the children separated from their parents to other children growing up with parents *in the rural area.* Parents trapped in rural areas earned 60% less than those who migrate, and our analysis shows that left-behind children fare even worse than this disadvantaged group. This is therefore a conservative estimate of the losses suffered by children who are sent back by migrant parents, relative to a counterfactual in which they would otherwise grow up with parents in the city, had the *hukou* restrictions not been so strict. Indeed, data from the China Family Panel Survey (CFPS) show that migrant children complete approximately one additional year of schooling, relative to children who grow up with parents in the village.

Second, female out-migration rates are lower in Gansu province – the site of our longitudinal analysis – and 85% of the left-behind children have their mother present. In contrast, the nationally representative CMDS data reveals that 60% of left-behind children grow up without *either parent present.* Our longitudinal analysis with Gansu data therefore again provides a conservative estimate of the costs imposed on left-behind children across China.

Third, our instrument - increases in labor demand in nearby cities - should otherwise benefit rural children by improving their parents' earnings capacity, remittance received, or even their own future economic opportunities. Especially children whose parents migrate and create a link to that growing city should benefit most. Import demand shocks in nearby cities should also increase returns to education and improve their incentives to invest in schooling. Despite those other positive channels of impact, we estimate detrimental effects on children left-behind, on net. The cost of parental separation is therefore likely even larger than what we document.

Fourth, since we study long-term outcomes in adulthood, we are forced to track individuals who were children a long time ago, in 2000. Children left-behind today face a very different environment. With improvements in infrastructure and transportation networks, migrants parents can now return home to see their children more frequently. With the advent of mobile technologies, migrant parents can communicate with left-behind children more regularly. On the other hand, those same smart-phone technologies in the hands of unsupervised children may be more dangerous today for their emotional and cognitive development.

To study the effects of parental absence on more recent cohorts of children, we use the later rounds of CFPS data to identify children born later, and can study the short-term effects of parental absence on their cognitive skills. Appendix Table A22 shows the reduced form: the interaction of world demand shocks and *hukou* restrictions also predictive of worse performance in vocabulary tests and maths test for school-aged children during 2010-2014. In other words, more recent cohorts of left-behind children also appear to be on the same trajectory, even if we cannot yet observe their long-run outcomes.

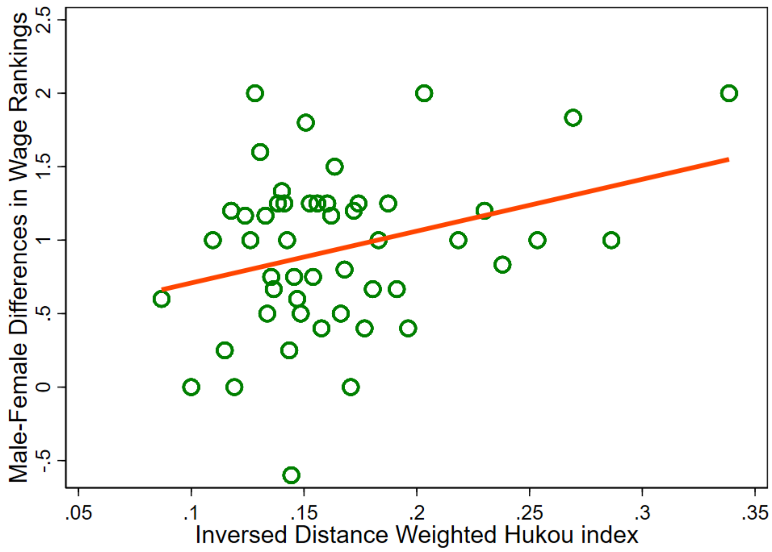
6.5 Hukou Restrictions and the Gender Wage Gap

Both our import demand and rainfall shock instruments capture the general economic drivers of parental migration, so they cannot separately identify any differential effect of parental absence on sons versus daughters. In order to shed light on the gender-differentiated long-term consequences of parents' greater propensity to leave daughters behind, we can use data from China Labor-force Dynamic Survey (CLDS) to examine whether there are larger gender differences in adult labor market outcomes for individuals who originate in rural areas adjacent to cities with stricter *hukou* restrictions (where parents exhibited the bias against daughters).

Figure 6 correlates *hukou* policy restrictiveness in nearby cities on the horizontal axis with a "gender wage gap" measure on the vertical axis.[18] In rural locations near restrictive *hukou* cities, there is a greater gender wage gap in earnings later in life. This is a natural and sensible implication of the two sets of results we showed in sections 4 and 6: migrant parents are more likely to leave daughters behind when they face a restrictive *hukou* environment, and the children left behind fare worse later in life. The joint implication of these two facts is that we should observe larger gender gaps in adult economic outcomes in rural areas adjacent to cities with restrictive *hukou* policies, which is exactly what Figure 6 shows.

[18] The gender wage gap is measured as the difference in wage rankings between male and female workers who have the same rural area of origin. We divide individual wages into three terciles to measure wage rankings.

Figure 6: *Hukou* Restrictions and Male-Female Wage Gaps



Notes: The figure illustrate how *hukou* restrictions in migrants' potential destination cities during individuals' childhood affect the gender gap in wages later in life. The horizontal axis denotes the inverse distance-weighted *hukou* index of potential destination cities (for migrants coming from a particular city of origin) when these individuals were at junior middle school age. The vertical axis shows differences in wage rankings between male and female workers who have the same city of origin. We divide individual wages into three tertiles to measure wage rankings. Cities are grouped into fifty groups according to the quantile of the inverse distance-weighted *hukou* index. Wage data come from the China Labor-force Dynamic Survey (CLDS), and data on the *hukou* index come from Zhang et al. (2019).

7 Mechanisms: Why are More Girls Left Behind?

In this section, we evaluate the underlying mechanisms through which *hukou* restrictions could lead to female children being left behind. At least four potential mechanisms may be responsible for the empirical patterns we report. First, *hukou* restrictions exacerbate the effects of pre-existing son preference, and daughters bear a disproportionate burden of the extra cost imposed on migrant parents. Second, the rate of return to education may be lower for females than males, so this is a rational parental response to market conditions. Third, sons are relatively more productive in cities, so parents optimally choose to keep boys in cities and girls in rural areas. Fourth, sons are expected to support parents in their old age, so parents invest more in their sons. We examine implications of each of these mechanisms, and find clearest support for the first one: that the decision to send daughters back is related to son-biased preferences.

7.1 Hukou Restrictions Exacerbate Pre-existing Son Preference

We first assess whether our empirical pattern is driven by the interplay between parental son preference and *hukou* restrictions. Table 7 assigns girls (of migrant households) into two groups, based on whether they have male siblings who will compete with them for limited educational resources in cities. We find that our main RD empirical result – daughters being left behind when they reach middle-school-age in restricted *hukou* cities – is only evident for those with male siblings. The empirical patterns we document therefore appear related to unequal intra-household allocation of resources between boys and girls.

We construct another heterogeneity test to explore whether gender-biased social norms explain the empirical patterns we report. We re-estimate our RD specification from Table 1 and additionally interact our independent variable of interest – girls above enrollment age in restrictive *hukou* cities – with the indicator for whether the male-female ratio of second births in migrant parents' provinces of origin is above the national mean. The observed male-female ratio of second births is thought to capture the level of son preference prevalent in rural Chinese provinces, because that' when parents are more likely to practice sex selection (Almond et al., 2019).[19] Table 8 shows that this triple interaction term is significantly positive for the sample of female children, which implies that the main RD result we documented in Table 1 (middle-school-aged girls left behind when migrants are in restrictive *hukou* cities) is significantly more pronounced for migrants who come from regions featuring son-biased sex ratios. The results are in accordance with the literature showing that, when people migrate, their beliefs and values on gender roles move with them, even though their external environment has changed (Alesina et al., 2013).

[19]To account for the confounding effects of current economic factors on gender ratio, we use the China Population Census 1990 (21 years prior to our sample period) to construct this interaction term. Almond et al. (2019) document that the sex ratio of second births measured using China Census 1990 reflects the son preference of parents, rather than differential potential earnings between male and female children.

Table 7: Heterogeneity by Whether Having Male Siblings

	(1)	(2)	(3)	(4)
Dependent Variable: Indicator for leaving the child in rural hometown				
	Has male siblings		Doesn't have male siblings	
School-aged × Highly restricted cities (=1) (ψ_1)	0.0372**	0.0365**	0.00585	0.00698
	(0.0171)	(0.0165)	(0.0295)	(0.0334)
School-aged (ψ_2)	0.00525	0.00781	0.0174	0.0253
	(0.0219)	(0.0226)	(0.0348)	(0.0401)
Observations	18,353	18,353	6,106	6,106
Adjusted R-squared	0.174	0.213	0.161	0.211
Household Control	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	No	Yes	No
City FE×Year FE×Hukou Province FE	No	Yes	No	Yes
Cohort FE	Yes	Yes	Yes	Yes
Age Bandwidth	2	2	2	2
Control function for the running variable	Linear	Linear	Linear	Linear

Notes: We use the sample of female children to estimate equation 1. Columns 1-2 show RD estimates for girls without male siblings, and columns 3-4 show RD estimates for girls with male siblings. The bandwidth is two years. We use a RD sample of children who are two years older or younger than the enrollment age of junior middle school. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. We use a local linear control function for the running variable. Robust standard errors clustered at the city level are reported in parentheses. *** significant at 1%; **significant at 5%; * significant at 10%.

7.2 Other Mechanisms

Differential Returns to Education or City Life? Men and women are likely to have heterogeneous returns to education, and one may expect that parents leave their female children in villages if females have a lower rate of return to education and therefore should be allocated less educational resources. In Table A23, we use individual-level data to perform Mincer wage regressions, and study whether the returns to high school education differ between men and women.[20] Table A23 shows that girls actually have a *higher* rate of return to education - both among rural families and urban families, and among migrants.

[20]We use individual-level pooled cross-sectional data by combining CLDS 2012, 2014, 2016 and 2018 to perform Mincer wage regression, because CLDS has a sample period similar to our baseline analysis and allows us to look at the pattern of gender-specific returns to education for people with different migration status and *hukou* types (rural or urban *hukou*).

Table 8: Heterogeneity by Baseline Sex Ratio in Original Provinces

	(1)	(2)	(3)	(4)
	Dependent variable: Indicator for leaving the child in rural hometown			
School-aged×Highly restricted cities (=1) ×	0.0680***	0.0664***	0.0820***	0.0812***
High Baseline Sex Ratio (=1)	(0.0222)	(0.0222)	(0.0169)	(0.0168)
Observations	31,066	31,066	31,066	31,066
Adjusted R-squared	0.101	0.102	0.206	0.207
Household Control	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	No	No
City FE×Year FE×Hukou Province FE	No	No	Yes	Yes
Cohort FE	No	Yes	No	Yes
Age Bandwidth	2	2	2	2
Control function for the running variable	Linear	Linear	Linear	Linear

Notes: The bandwidth is two years. We use RD sample that are two years older or younger than the enrollment age of junior middle school. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. We use a local linear control function for the running variable. High baseline sex ratio is an indicator for whether the male-female ratio of second births in migrant parents' *hukou* provinces is above the national mean level. Robust standard errors clustered at the city level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A related possibility is that working in cities offers boys larger marginal returns compared to girls, and it is therefore economically rational for parents to give their sons greater exposure and access to cities. We use information on individual incomes in CLDS surveys to estimate gender-specific returns to migration for a sample of rural *hukou* in Table A24. The returns to working in cities is actually significantly larger for girls compared to boys.[21]

These correlations make it highly unlikely that the stronger propensity to leave daughters behind in rural areas (which undermines their educational attainment and future work opportunities in cities) stems from sons producing greater returns from education or from remaining in the city.

Sons are More Valuable for Old-Age Support? If sons (but not daughters) are expected to support elderly parents, migrants may rationally respond by keeping their sons with them, and leave daughters behind. To test this hypothesis, we use

[21] A concern with that test is endogenous selection into migration, or the "Roy sorting bias". We apply the Dahl (2002) selection correction procedure in Table A24 to address this, and find that the returns to migration remains significantly larger for girls compared to boys.

the CFPS data to create an indicator for whether the share of old people (aged 60 years or above) that are supported by their sons in a particular province is above the national mean. Table A25 shows that the effects of *hukou* restrictions on girls being left behind are not meaningfully affected the strength of the social norm that sons provide old-age support.

Girls are just different than boys? If parents fear that the uncertainties created by migrant restriction policies that cities have been adopting would have a more detrimental effect on girls, or that cities are more dangerous for girls, or that it is easier for grandparents to raise girls than boys in the rural hometown, then they may be more likely to leave daughters behind. Our identification strategy – where we show that parents' propensity to send daughters back from *hukou* restricted cities once they enter middle-school age – suggest that fixed differences between boys and girls are unlikely to explain the patterns we document. Parents do not always treat girls differently; only when and where their child becomes more expensive to keep.

In sum, the interaction between pre-existing son-biased preferences and migration restrictions provides the most credible, concise explanation for Chinese migrant parents' propensity to leave daughters behind when it becomes costly to keep their children with them in the city. Such son preference may itself be a result of historical gaps in earnings and productivity by gender. But current *Hukou* policies serve to perpetuate and exacerbate those gender inequities.

8 Conclusion

Our analysis highlights an unintended consequence of imposing mobility restrictions on gender inequality. As economic growth and industrial activities increase demand for unskilled workers in Chinese cities, adult migrant workers without a local *hukou* move to urban areas for work, but migration policies are designed to make it difficult for those parents to keep their children with them. That forces poor migrants into a difficult choice: is it worth the expense of keeping my child with me? If there is some pre-existing gender bias in the population, then the cost of the choices that migrants are forced into will be borne disproportionately by girls. We show that migrants are more likely to leave behind their daughters than their sons in poor rural areas. And this in turn perpetuates gender inequality inter-generationally, as left-behind children suffer later in life with worse educational attainment and lower socio-economic status.

Other studies have documented that mobility constraints trigger economic losses for adult workers and widen economic gaps between rural and urban people. We additionally highlight a distributional consequence that is gendered. Our work proposes a new mechanism whereby placing restrictions on migration can exacerbate gender inequity, even if the migration policy does not have an explicit gender dimension.

We already knew that improved access to economic opportunities for females and disadvantaged groups has significantly boosted economic growth in the United States (Duflo, 2012; Hsieh et al., 2019). A new corollary, given our results, is that migration restrictions can undermine long-term economic development in China and other developing countries. Both aggregate and distributional effects of mobility restrictions may be larger than development economists previously thought.

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Appendix

Table of Contents

A1 Summary Statistics of Key Variables

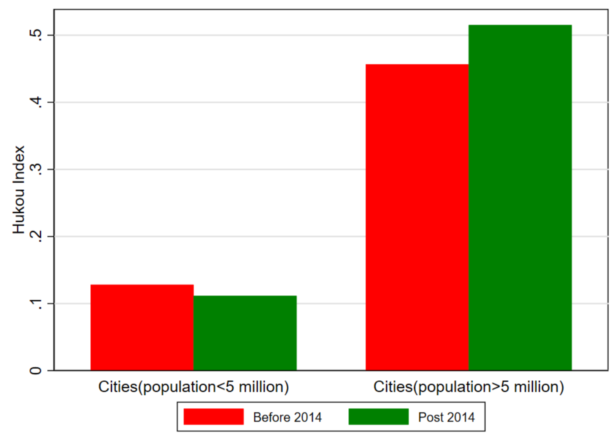
Table A1: Summary Statistics of Key Variables

Variable name	Mean	Std. dev
Panel A		
Leave Children Behind (=1)	0.343	0.475
Amount of Remittance (Chinese Yuan)	4755.343	7131.414
Age of Children	10.928	2.631
Birth Month of Children	6.662	3.487
Age of Father	36.52	5.300
Panel B		
Years of Schooling	11.37	3.510
Pass High School Entrance Exams (=1)	0.673	0.469
Low Income Group (=1)	0.493	0.500
Level of Distraction	2.771	0.844
Capability to Coping with Stress	3.594	0.735
Obesity (BMI>30)	0.0261	0.160
A Grandparent was Alive (=1)	0.786	0.410
A Grandparent was Living in the Same Place (=1)	0.938	0.242

Notes: Table shows summary statistics for most outcomes, independent variables and control variables. Data on the variables in panel A come from the China Migrants Dynamic Survey (CMDS), and data on the variables in panel B come from the Gansu Survey of Children and Families (GSCF). We divide the children in our sample into two groups based on their income in 2015; the low-income group includes those whose income is below the bottom quartile of 2015 income distribution for people who were born in Gansu and those who do not have any income (columns 1 and 2). We use the CFPS data to look at the 2015 income distribution for people who were born in Gansu. In GSCF 2015, there is a survey question: Are you more easily distracted (1=strongly disagree; 2= disagree; 3= neither agree nor disagree; 4=agree; 5=strongly agree). Based on this question we define the level of distraction (columns 3 and 4): =1 if the answer is strongly disagree;...; =5 if the answer is strongly agree. There is another survey question in GSCF: Are you able to cope with stress (1=strongly disagree; 2= disagree; 3= neither agree nor disagree; 4=agree; 5=strongly agree). Based on this question we define the capability of coping with stress (columns 5 and 6): =1 if the answer is strongly disagree;..; =5 if the answer is strongly agree.

A2 Important Facts about Context and Educational System

Figure A1: 2014 Population Control Policy and *Hukou* Restrictions



Notes: We divide cities into two groups based on whether baseline population in the city central district area is above 5 million. Data the *hukou* index come from Zhang et al. (2019).

Table A2: The Share of Teachers by Education Levels

	Master or above	College	Pre-college	High school	Below high school
			Panel A: Junior middle school		
Urban	0.031	0.830	0.135	0.003	0.000
Rural	0.004	0.657	0.328	0.011	0.000
			Panel B: Primary school		
Urban	0.010	0.570	0.374	0.045	0.000
Rural	0.001	0.249	0.552	0.195	0.003

Notes: Data come from the *Educational Statistics Yearbook of China* 2013.

Table A3: The Share of Teachers by Professional Titles

	Special Grade (Excellent)	Level-1	Level-2	Level-3	No title
Panel A: Junior middle school					
Urban	0.218	0.436	0.270	0.009	0.068
Rural	0.114	0.405	0.372	0.026	0.083
Panel B: Primary school					
Urban	0.578	0.302	0.022	0.003	0.095
Rural	0.508	0.360	0.041	0.002	0.089

Notes: Professional titles are designated to teachers based on their professionalism and progressive nature. The special grade teacher is the highest professional title, followed by Level-1 teacher, and then by Level-2 and Level-3 teacher. Data come from the *Educational Statistics Yearbook of China* 2013.

Table A4: Education Facilities per Student

	Num of multi-media classrooms	Asset value of education equipment
Panel A: Junior Middle School		
Urban	0.053	0.511
Rural	0.036	0.358
Panel B: Primary School		
Urban	0.081	0.653
Rural	0.036	0.293

Notes: Data come from the *Educational Statistics Yearbook of China* 2013.

Table A5: Beijing Closed Migrant Schools in Recent Years

Year	Number of migrant children in Beijing (10,000)	Share of migrant children in migrant schools	Number of Migrant Schools
2006	37.5	34.7	300
2007	40.0	36.5	268
2008	40.0	34.0	228
2010	43.4	—	—
2011	47.8	27.2	176
2012	41.9	—	158
2013	52.9	24.2	130
2014	51.1	18.2	127

Notes: Data come from the *Annual Report on Education for the China's Migrant Children* (2016).

Table A6: Migrant Households' Spending on Education

	Primary school	Junior middle school
Zanzhufei specific for migrant children	1432.005	2198.48
Total education expenditure (excluding *zanzhufei*)	1444.093	2339.375

Notes: In China, migrant children without a local *hukou* have to pay *zanzhufei* (an extra fee specifically imposed on them) in order to go to a local school. Data come from the *Chinese Household Income Project Survey* (*CHIPS*) 2007 *and* 2008.

Table A7: Migrant Children in Guangzhou Disappear as They Enter Junior Middle School

		2008	2012	2015
Primary school	Num of migrant children	376963	434473	458216
	Share of migrant children	43.69%	52.82%	48.86%
Junior middle school	Num of migrant children	86089	121426	127815
	Share of migrant children	21.09%	32.51%	37.97%
High school Entrance Exam	Num of migrant children	—	23762	31969
	Share of migrant children	—	20.06%	28.87%

Notes: Only a small fraction of migrant children without a local *hukou* are eligible to take local high-school entrance exams. Every year, the Guangzhou government sets a quota for the number of migrant children who can take local high-school entrance exams. Data come from the *Annual Report on Education for China's Migrant Children* (2016).

A3 Additional Results of First RD Design

Table A8: Summary Statistics of Observables for Below and Above the Age Cutoff

	(1) Below age cutoff	(2) Above age cutoff	(3) Diff. in means	(4) RD Estimates
	Panel A: Boys			
Household *hukou* transfer (=1)	0.006	0.003	-0.003	-0.010
	(0.078)	(0.054)	[0.003]	[0.007]
Father migrates (=1)	0.014	0.009	-0.005	-0.027
	(0.117)	(0.092)	[0.009]	[0.035]
Mother migrates (=1)	0.018	0.018	-0.000	-0.008
	(0.135)	(0.133)	[0.010]	[0.039]
Father income (=1)	37,288.474	30,975.676	-6,312.798*	-6,720.214
	(23,504.601)	(23,217.771)	[3,253.024]	[13,079.839]
Mother income (=1)	21,312.289	21,306.623	-5.666	8,199.975
	(14,738.911)	(17,566.470)	[2,327.219]	[10,131.891]
	Panel B: Girls			
Household *hukou* transfer (=1)	0.003	0.002	-0.001	0.006
	(0.052)	(0.041)	[0.002]	[0.008]
Father migrates (=1)	0.009	0.010	0.001	0.000
	(0.096)	(0.101)	[0.008]	[0.032]
Mother migrates (=1)	0.023	0.031	0.008	-0.037
	(0.149)	(0.173)	[0.013]	[0.052]
Father income (=1)	35,217.738	35,613.582	395.844	-7,051.000
	(22,727.107)	(23,917.980)	[3,333.514]	[11,393.291]
Mother income (=1)	21,669.966	19,778.509	-1,891.457	-9,579.064
	(15,597.513)	(15,566.202)	[2,430.097]	[8,001.999]

Notes: Household *hukou* transfer is an indicator for whether a particular household transfers their *hukou* location. Father migrates and Mother migrates are indicators for whether father and mother, respectively, move away from their *hukou* city. Columns 1 and 2 report the sample mean and standard deviation for children whose ages are above and below the age cutoff, respectively. Column 3 reports the raw difference between these sample means. Note that this statistic shows a simple difference between all children aged 6-15, which is not necessarily a discontinuous difference at the RD cutoff. In column 4, we use our RD sample to investigate whether there is such a discontinuous difference. We use local linear regression to obtain RD estimates for the observables and report the standard errors in brackets. In columns 1 and 2, standard deviations are reported in parentheses. In columns 3 and 4, standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Data Manipulation Test

	(1)	(2)	(3)
	All	Female	Male
T-stat	0.3518	-0.3835	0.7948
P-value	(0.7250)	(0.7014)	(0.4267)

Notes: This table reports the density test at the cutoff of school enrollment age using the method proposed by Cattaneo et al. (2020). T-statistics of the RD density test and corresponding p-values in parentheses are reported.

Table A10: Alternative RD Control and Different Bandwidth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Indicator for leaving the child in rural hometown							
	Female	Male	Female	Male	Female	Male	Female	Male
Panel A: Quadratic Control+2-year Bandwidth								
School-aged × Highly restricted cities (=1) (ψ_1)	0.0324**	0.00331	0.0330**	0.00444	0.0349**	0.00871	0.0354**	0.00984
	(0.0145)	(0.0150)	(0.0144)	(0.0148)	(0.0145)	(0.0170)	(0.0144)	(0.0167)
Observations	31,071	40,854	31,071	40,854	31,071	40,854	31,071	40,854
Adjusted R-squared	0.172	0.146	0.173	0.147	0.206	0.184	0.207	0.184
Panel B: Quadratic Control+3-year Bandwidth								
School-aged × Highly restricted cities (=1) (ψ_1)	0.0261*	0.0161	0.0269*	0.0167	0.0268*	0.0187	0.0274*	0.0193
	(0.0146)	(0.0148)	(0.0144)	(0.0145)	(0.0144)	(0.0159)	(0.0142)	(0.0154)
Observations	47,040	61,572	47,040	61,572	47,040	61,572	47,040	61,572
Adjusted R-squared	0.176	0.152	0.177	0.152	0.208	0.187	0.209	0.188
Panel C: Local Linear Control+3-year Bandwidth								
School-aged × Highly restricted cities (=1) (ψ_1)	0.0261*	0.0162	0.0269*	0.0168	0.0268*	0.0188	0.0274*	0.0193
	(0.0146)	(0.0149)	(0.0144)	(0.0145)	(0.0144)	(0.0159)	(0.0142)	(0.0154)
Observations	47,040	61,572	47,040	61,572	47,040	61,572	47,040	61,572
Adjusted R-squared	0.176	0.152	0.177	0.152	0.208	0.187	0.209	0.188
Household Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	Yes	Yes	No	Yes	No	No
City FE×Year FE×*Hukou* Province FE	No	No	No	No	Yes	No	Yes	Yes
Cohort FE	No	No	Yes	Yes	No	Yes	Yes	Yes

Notes: This table shows the results of estimating equation 1. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. Robust standard errors clustered at the city level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Triple Difference Regressions

	(1)	(2)	(3)	(4)
	Dependent variable: Indicator for leaving the child in rural hometown			
Female × School-aged × Highly restricted cities (=1)	0.0282*	0.0279*	0.0282*	0.0279*
	(0.0152)	(0.0151)	(0.0152)	(0.0151)
Observations	71,925	71,925	71,925	71,925
Adjusted R-squared	0.157	0.158	0.157	0.158
Household Control	Yes	Yes	Yes	Yes
City FE × Year FE	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	No	Yes
Age Bandwidth	2	2	2	2
Control function for the running variable	Linear	Linear	Quadratic	Quadratic

Notes: The bandwidth is two years. We use a RD sample of children who are two years older or younger than the enrollment age of junior middle school. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. Robust standard errors clustered at the city level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Estimates using the Sample of First-born Children

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Indicator for leaving the child in rural hometown							
	Female	Male	Female	Male	Female	Male	Female	Male
School-aged × Highly restricted cities (=1)	0.0366**	0.00864	0.0374**	0.00974	0.0413**	0.0131	0.0418**	0.0141
	(0.0155)	(0.0159)	(0.0154)	(0.0158)	(0.0170)	(0.0188)	(0.0170)	(0.0185)
Observations	27,370	34,234	27,370	34,234	27,370	34,234	27,370	34,234
Adjusted R-squared	0.172	0.141	0.173	0.142	0.203	0.175	0.203	0.176
Mean of Dep. Var.	0.36	0.35	0.36	0.35	0.36	0.35	0.36	0.35
Household Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	Yes	Yes	No	No	No	No
City FE×Year FE×Hukou Province FE	No	No	No	No	Yes	Yes	Yes	Yes
Cohort FE	No	No	Yes	Yes	No	No	Yes	Yes
Age Bandwidth	2	2	2	2	2	2	2	2
Control function for the running variable	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear

Notes: This table shows the results of estimating equation 1 using the sample of first-born children. The bandwidth is two years. We use a RD sample of children who are two years older or younger than the enrollment age of junior middle school. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. We use a local linear control function for the running variable. Robust standard errors clustered at the city level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Controlling for the Number of Children

	(1)	(2)	(3)	(4)
Dependent Variable: Indicator for leaving the child in rural hometown				
	Female	Male	Female	Male
Panel A: Control for the number of children				
School-aged × Highly restricted cities (=1) (ψ_1)	0.0329**	0.00444	0.0359**	0.00984
	(0.0142)	(0.0148)	(0.0141)	(0.0167)
School-aged (ψ_2)	-0.00463	0.00125	-0.00635	0.000597
	(0.0156)	(0.0134)	(0.0174)	(0.0152)
Observations	31,071	40,854	31,071	40,854
Adjusted R-squared	0.175	0.147	0.210	0.184
Panel B: Control for FE for the number of children				
School-aged × Highly restricted cities (=1) (ψ_1)	0.0331**	0.00473	0.0359**	0.0107
	(0.0141)	(0.0148)	(0.0141)	(0.0169)
School-aged (ψ_2)	-0.00468	0.00134	-0.00637	0.000901
	(0.0156)	(0.0133)	(0.0175)	(0.0152)
Observations	31,071	40,854	31,071	40,854
Adjusted R-squared	0.175	0.148	0.210	0.187
Household Control	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	No	No
City FE×Year FE×Hukou Province FE	No	No	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes

Notes: The bandwidth is two years. We use a RD sample of children who are two years older or younger than the enrollment age of junior middle school. We control for the number of children in panel A, fixed effects for child number in panel B, and gender wage gaps in both the origin and destination of migrant parents in panel C. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. We use a local linear control function for the running variable. Robust standard errors clustered at the city level are reported in parentheses. *** significant at 1%; **significant at 5%; * significant at 10%.

Table A14: Controlling for the Effect of the OCP

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Indicator for leaving the child in rural hometown					
	Female	Male	Female	Male	Female	Male
School-aged × Highly restricted cities (=1) (ψ_1)	0.0338**	0.00713	0.0342**	0.00889	0.0341**	0.00724
	(0.0154)	(0.0147)	(0.0154)	(0.0142)	(0.0159)	(0.0144)
Observations	33,041	43,470	32,498	42,616	32,498	42,616
Adjusted R-squared	0.210	0.181	0.208	0.180	0.218	0.188
Household Control	Yes	Yes	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Father Race FE×Year FE×Father *Hukou* Province FE	Yes	Yes	No	No	Yes	Yes
Mother Race FE×Year FE×Mother *Hukou* Province FE	No	No	Yes	Yes	Yes	Yes
Age Bandwidth	2	2	2	2	2	2
Control function for the running variable	Linear	Linear	Linear	Linear	Linear	Linear

Notes: This table shows the results of estimating equation 1. The bandwidth is two years. We use a RD sample of children who are two years older or younger than the enrollment age of junior middle school. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. We use a local linear control function for the running variable. Robust standard errors clustered at the city level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A4 Additional Results of Mega-city RD Design

Table A15: Migration Responses to 2014 Mega City Population Controls

	(1)	(2)	(3)
Dependent Variable: Change city location Indicator			
I(Population>5 million) × I(Year>2014)	0.00290		
× Having a school-aged child (=1)	(0.00437)		
I(Population>5 million) × I(Year>2014)		0.00416	
×Having a school-aged daughter (=1)		(0.00797)	
I(Population>5 million) × I(Year>2014)			0.00151
×Having a school-aged son (=1)			(0.00211)
Observations	11,382	11,382	11,382
Adjusted R-squared	0.955	0.955	0.955
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City Size Bandwidth	3	3	3

Notes: We employ individual longitudinal panel data from 2011 to 2016 constructed using China Labor-force Dynamic Survey. The dependent variable is an indicator for whether for a particular migrant parent changed city location between year t and $t-1$. I(Population>5 million) is an indicator for the migrant parent was in a mega city in year $t-1$. I(Year>2014) is an indicator for is an indicator for the post-treatment period. Having a school-aged child (=1) is an indicator for whether the parent had a child who had reached the middle-school age in year $t-1$. We control for the interactions between any two of the three indicators (in the triple interaction term) as well as the three indicators. The city size bandwidth is 3 million. We only include cities with population within 2 million and 8 million. Robust standard errors clustered at the city level are reported in parentheses. *** significant at 1%; **significant at 5%; * significant at 10%.

Table A16: Different Coming year

	(1)	(2)	(3)	(4)
Dependent Variable: Indicator for leaving the child in rural hometown				
	Female	Male	Female	Male
Panel A: Come before 2014				
School-aged ×I(Population>5 million) ×	0.0700***	-0.0429	0.0772**	-0.0314
I(Year>2014)	(0.0220)	(0.0363)	(0.0306)	(0.0267)
Observations	10,296	13,812	10,296	13,812
Adjusted R-squared	0.163	0.137	0.192	0.169
Panel B: Come before 2013				
School-aged ×I(Population>5 million) ×	0.0913***	-0.0641	0.0966***	-0.0496
I(Year>2014)	(0.0298)	(0.0387)	(0.0332)	(0.0304)
Observations	9,629	12,815	9,629	12,815
Adjusted R-squared	0.163	0.135	0.193	0.170
Panel C: Come before 2012				
School-aged ×I(Population>5 million) ×	0.0661**	-0.0689	0.0696**	-0.0569
I(Year>2014)	(0.0254)	(0.0426)	(0.0286)	(0.0329)
Observations	8,626	11,466	8,626	11,466
Adjusted R-squared	0.158	0.130	0.187	0.166
Household Control	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	No	No
City FE×Year FE×*Hukou* Province FE	No	No	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Age Bandwidth	2	2	2	2
City Size Bandwidth	3	3	3	3

Notes: The age bandwidth is two years. We use a RD sample of children who are two years older or younger than the enrollment age of junior middle school. The city size bandwidth is 3 million. We only include cities with population within 2 million and 8 million. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. We use a local linear control function for the running variable. Robust standard errors clustered at the city level are reported in parentheses. *** significant at 1%; **significant at 5%; * significant at 10%.

A5 Additional Results on Remittance Behaviour

Table A17: Differential Remittance by the Gender of First-born Children

	(1)	(2)	(3)	(4)
	Dependent variable: IHS of the Amount of Remittance			
Panel A: Full Sample				
Female	-0.134***	-0.134***	-0.154***	-0.154***
	(0.0375)	(0.0374)	(0.0419)	(0.0417)
Observations	30,365	30,365	30,365	30,365
Adjusted R-squared	0.0692	0.0698	0.0918	0.0926
Panel B: Primary School Age				
Female	-0.110*	-0.111*	-0.112	-0.111
	(0.0637)	(0.0637)	(0.0694)	(0.0692)
Observations	11,175	11,175	11,175	11,175
Adjusted R-squared	0.0694	0.0693	0.0938	0.0938
Panel C: Junior Middle School Age				
Female	-0.152**	-0.154**	-0.170**	-0.170**
	(0.0684)	(0.0678)	(0.0715)	(0.0708)
Observations	7,646	7,646	7,646	7,646
Adjusted R-squared	0.0786	0.0783	0.101	0.100
Household Control	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	No	No
City FE×Year FE×*Hukou* Province FE	No	No	Yes	Yes
Cohort FE	No	Yes	No	Yes

Notes: We use the sample of first-born children. The Inverse Hyperbolic Sine (IHS) transformation is applied to the amount of remittance. Panel A shows results for all first-born children aged below 16, and panels B and C, respectively, show results for first-born children at primary school age and junior middle school age. We use the CMDS 2011 and 2012 to perform estimation as only the two waves of CMDS contain information about remittance. Robust standard errors clustered at the city level are reported in parentheses. *** significant at 1%; **significant at 5%; * significant at 10%.

A6 Additional Results on Long-term Consequences

Table A18: First-Stage Estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Indicator for leaving the child in rural hometown				IHS of the amount of time that parents are away			
WID × High hukou restrictions	1.053***	1.048***			1.906***	1.891***		
	(0.153)	(0.171)			(0.528)	(0.581)		
Log rainfall × Migration ties			-3.588***	-3.518***			-3.389***	-3.140***
			(0.332)	(0.408)			(0.649)	(0.944)
Observations	1,379	1,379	1,414	1,414	1,379	1,379	1,414	1,414
Adjusted R-squared	0.126	0.125	0.126	0.125	0.146	0.146	0.149	0.149
F stat	47.55	37.70	116.8	74.26	13.02	10.61	27.29	11.06
Household Controls	No	Yes	No	Yes	No	Yes	No	Yes
Township FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Household controls include the number of children, an indicator for whether a grandparent was alive, and an indicator for whether a grandparent was living in the same place. We control for WID in columns 1, 2, 5, and 6, and Log rainfall in columns 3, 4, 7 and 8. The Inverse Hyperbolic Sine (IHS) transformation is applied to the amount of time that parents are away (columns 5-8). Robust standard errors clustered at the prefecture of birth level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A19: Reduced Form Results of Educational Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Years of Schooling		IHS of Years of Schooling		Pass High School Entrance Exams (=1)	
WID × Highly *hukou* restrictions	-3.008***	-3.151***	-0.291***	-0.304***	-0.505**	-0.552**
	(0.705)	(0.669)	(0.0685)	(0.0785)	(0.179)	(0.211)
Observations	1,335	1,335	1,335	1,335	946	946
Adjusted R-squared	0.0919	0.0997	0.0777	0.0846	0.0232	0.0299
Mean of Dep. Var.	11.37	11.37	3.067	3.067	0.673	0.673
SD of Dep. Var.	3.510	3.510	0.381	0.381	0.469	0.469
Mean of WID	0.0989	0.0910	0.0989	0.0989	0.101	0.101
SD of WID	0.0910	0.0989	0.0910	0.0910	0.0900	0.0900
Household Controls	No	Yes	No	Yes	No	Yes
Township FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Household controls include an indicator for whether a grandparent was alive and an indicator for whether a grandparent was living in the same place. We control for WID. Like Khanna et al. (2020), we also control for import tariffs which may affect firm productivity. The Inverse Hyperbolic Sine (IHS) transformation is applied to years of schooling (columns 3 and 4). We restrict our sample to those who had taken high school entrance exams in columns 5 and 6. Robust standard errors clustered at the prefecture of birth level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A20: Alternative Instrumental Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Years of Schooling		IHS of Years of Schooling		Pass High School Entrance Exams (=1)	
Indicator for leaving the child behind	-3.603**	-4.034**	-0.332**	-0.370**	-0.489**	-0.580***
	(1.273)	(1.494)	(0.127)	(0.159)	(0.160)	(0.171)
F stat	102.6	74.61	102.6	74.61	43.67	41.83
Observations	1,366	1,366	1,366	1,366	966	966
Mean of Dep. Var.	11.34	11.34	3.065	3.065	0.675	0.675
SD of Dep. Var.	3.496	3.496	0.380	0.380	0.469	0.469
Household Controls	No	Yes	No	Yes	No	Yes
Township FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Instrumental variable specification using the interaction of rainfall with historical migration ties. We drop observations with missing values in the dependent variables. We control for other weather conditions, including sunshine, temperature, and humidity. Household controls include an indicator for whether a grandparent was alive and an indicator for whether a grandparent was living in the same place. The Inverse Hyperbolic Sine (IHS) transformation is applied to years of schooling (columns 3 and 4). Robust standard errors clustered at the prefecture of birth level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A21: Alternative Measure of Leaving Children Behind

	(1)	(2)	(3)	(4)	(5)	(6)
	Years of Schooling		IHS of Years of Schooling		Pass High School Entrance Exams (=1)	
IHS of the amount of time that parents are away	-1.640***	-1.727**	-0.159**	-0.167*	-0.247*	-0.266
	(0.463)	(0.593)	(0.0598)	(0.0748)	(0.131)	(0.159)
F stat	17.39	14.69	17.39	14.69	11.60	12.07
Observations	1,335	1,335	1,335	1,335	946	946
Mean of Dep. Var.	11.37	11.37	3.067	3.067	0.673	0.673
SD of Dep. Var.	3.510	3.510	0.381	0.381	0.469	0.469
Household Controls	No	Yes	No	Yes	No	Yes
Township FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes Instrumental variables specification using the interaction of World Import Demand (WID) and *hukou* restrictions. We drop observations with missing values in the dependent variables. Household controls include an indicator for whether a grandparent was alive and an indicator for whether a grandparent was living in the same place. Like Khanna et al. (2020), we control for import tariffs which may affect firm productivity. The Inverse Hyperbolic Sine (IHS) transformation is applied to the amount of time that parents are away (the independent variable of interest) and years of schooling (the dependent variable in columns 3 and 4). Robust standard errors clustered at the prefecture of birth level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A22: Effects on Children Born Recently

	(1)	(2)	(3)	(4)
Panel A Dep Var: Good Performance in Vocabulary Test (=1)				
WID $\times$ Highly *hukou* restrictions	-0.126**	-0.115**	-0.115**	-0.115**
	(0.0519)	(0.0516)	(0.0516)	(0.0516)
Observations	1,833	1,833	1,833	1,833
Adjusted R-squared	0.441	0.469	0.469	0.469
Mean of Dep. Var.	0.242	0.242	0.242	0.242
SD of Dep. Var	0.429	0.429	0.429	0.429
Panel B Dep Var: Good Performance in Math Test (=1)				
WID $\times$ Highly *hukou* restrictions	-0.119**	-0.113**	-0.113**	-0.113**
	(0.0551)	(0.0552)	(0.0552)	(0.0552)
Observations	1,833	1,833	1,833	1,833
Adjusted R-squared	0.436	0.441	0.441	0.441
Mean of Dep. Var.	0.241	0.241	0.241	0.241
SD of Dep. Var.	0.428	0.428	0.428	0.428
Mean of WID	0.273	0.273	0.273	0.273
SD of WID	0.361	0.361	0.361	0.361
Birth City FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Cohort FE	No	Yes	Yes	No
Year by Cohort FE	No	No	No	Yes

Notes: We use pooled cross-sectional data by combining CFPS 2010 and 2014, as the two waves of CFPS conducted vocabulary and math tests for school-aged children. We use the sample of children at junior middle school age. Good performance in vocabulary test (=1) is an indicator for whether the performance of a particular child in vocabulary test ranks top 25% of children born in the same city. Good Performance in Math test (=1) is an indicator for whether the performance of a particular child in Math test ranks top 25% of children born in the same city.Like Khanna et al. (2020), we control for import tariffs which may affect firm productivity. Robust standard errors clustered at the city level are reported in parentheses. *** significant at 1%; **significant at 5%; * significant at 10%.

A7 Tests of Alternative Mechanisms (from Section 7)

Table A23: Differential Returns to Education by Gender

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Log individual income				
	Full Sample	Rural *hukou* holders	Urban *hukou* holders	Migrants	Locals
High school (=1)	0.217***	0.110***	0.300***	0.251***	0.195***
	(0.0142)	(0.0185)	(0.0301)	(0.0243)	(0.0178)
High school (=1) × Female (=1)	0.185***	0.118***	0.121***	0.148***	0.205***
	(0.0196)	(0.0264)	(0.0403)	(0.0329)	(0.0249)
Observations	30,021	21,860	8,161	9,740	19,842
Adjusted R-squared	0.381	0.360	0.297	0.378	0.354
City FE × Year FE	Yes	Yes	Yes	Yes	Yes

Notes: We use individual-level pooled cross-sectional data by combining CLDS 2012, 2014, 2016 and 2018. We control for an indicator for female, an indicator for rural *hukou*, age and age-squared. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A24: Differential Returns to Migrating to Cities by Gender

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Log individual income					
Migrate to Cities (=1)	0.242***	0.236***	0.224***	0.217***	0.224***	0.217***
	(0.0276)	(0.0276)	(0.0288)	(0.0289)	(0.0288)	(0.0289)
Migrate to Cities (=1) × Female (=1)	0.113***	0.117***	0.111***	0.116***	0.110***	0.115***
	(0.0298)	(0.0298)	(0.0301)	(0.0301)	(0.0301)	(0.0301)
Observations	16,046	16,046	16,046	16,046	16,046	16,046
Adjusted R-squared	0.364	0.367	0.366	0.369	0.367	0.369
City FE × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	No	Yes	No	Yes
Hukou Location FE	No	No	Yes	Yes	Yes	Yes
Dahl Correction	No	No	No	No	Yes	Yes

Notes: We use individual-level pooled cross-sectional data by combining CLDS 2012, 2014, 2016 and 2018 and restrict the sample to rural *hukou* holders. We control for an indicator for female, an indicator for high school and above, age and age-squared. To address the endogeneity of migration choices, we apply the Dahl (2002) semi-parametric selection correction approach in columns 5 and 6. We divide individuals into groups based on *hukou* regions, gender and education levels at baseline. Then, we define baseline selection probability ω_i as the fraction of the population in individual i's cell that chooses to live in a particular destination city. Finally, we augment the Mincer equation by adding a quadratic function of ω_i. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A25: Heterogeneity by the Norm that Aged Parents Are Supported by Sons

	(1)	(2)	(3)	(4)
Dependent Variable: Indicator for leaving the child in rural hometown				
School-aged × Highly restricted cities (=1)	0.000356	-0.00104	-0.0150	-0.0172
×Strong norm that the aged are supported by sons (=1)	(0.0214)	(0.0216)	(0.0227)	(0.0229)
Observations	29,336	29,336	29,336	29,336
Adjusted R-squared	0.162	0.163	0.191	0.192
Household Control	Yes	Yes	Yes	Yes
City FE×Year FE	Yes	Yes	No	No
City FE×Year FE×Hukou Province FE	No	No	Yes	Yes
Cohort FE	No	Yes	No	Yes
Age Bandwidth	2	2	2	2
Control function for the running variable	Linear	Linear	Linear	Linear

Notes: The bandwidth is two years. We use a RD sample of children who are two years older or younger than the enrollment age of junior middle school. Household controls include father's age and age-squared, an indicator for whether household income is above the median value among the migrant population in the city and an indicator for whether household consumption is above the median value among the migrant population in the city. We create an indicator for whether the share of people aged 60 years or above that are supported by their sons in a particular province is above the national mean. We use a local linear control function for the running variable. Robust standard errors clustered at the city level are reported in parentheses. *** significant at 1%; **significant at 5%; * significant at 10%.