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Article

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Children Left Behind in China: The Role of School Fees

Abstract

The barriers faced by Chinese rural–urban migrants to access social services, particularly education, in host cities could help explain why the majority of them choose to leave their children behind. We identified the causal impacts of school fees by instrumenting for it with unexpected shocks to the city’s public education spending. Our findings suggest that higher fees deter migrant workers from bringing their children with them, especially their daughters, reduce the number of children they bring, and increase educational remittances to rural areas for the children left behind. Increases in school fees mostly affect vulnerable migrant workers and could have stronger impacts during an economic crisis. These findings hold for different model specifications and robustness checks.

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1 Introduction

Migrant workers account for as much as half of the total urban labor force in China. Yet, due to the *hukou* (household registration) system, they are granted limited or no access to the subsidized education and other social services available to local city residents. This results in many migrants leaving their children behind when migrating to cities for work. Indeed, more than one-fourth of all children in China aged 0–17 years—amounting to almost 70 million children—are estimated to be left behind by their migrant parents (UNICEF, 2018).¹

Parental migration is observed to have both positive and negative impacts on their LBC in different countries.² Recent studies on China, however, overwhelmingly point to the detrimental impacts of parental migration on LBC on a variety of outcomes in education achievement including enrollment (Wang, 2014), grade attainment (Meyerhoefer and Chen, 2011), and standardized test scores (Zhang et al., 2014; Zhou et al., 2014) and in health, including overweight and underweight measures (de Brauw and Mu, 2011) and anxiety levels and self-esteem (Bai et al., 2016). In addition to having worse education and health outcomes, Meng and Yamauchi (2017) also found that LBC spend less time studying after school, receive fewer tutoring lessons outside school, and are more likely to be enrolled in lower quality schools. These findings, however, contrast with (Chen et al. 2009), who reported evidence of the positive impacts of parental migration, and Mu and de Brauw (2015), who found that parental migration has no significant effect on the height of children but has positive effects on their weight.

Yet, regardless of which way one might interpret the existing evidence, the LBC phenomenon has attracted much attention from the media, most notably about the psychological costs of family separation that can potentially lead to suicides of LBC (see, for example, Xinhua News Agency (2015) and *The Economist* (2015a, 2015b, 2016)). The Government of China has thus unsurprisingly set a priority to make urbanization “more inclusive” for migrant workers and their families (World Bank and DRC, 2014).

In this paper, we study how an important factor—school fees—determines parents’ decision whether to bring their children with them when migrating to a city. To identify the causal impacts of school fees, we used a novel instrument: the unexpected shocks to public spending on education. Estimation results suggest that increased school fees decrease both the probability that migrant households bring their children to the city and the number of children they bring, as well as the likelihood that they bring a daughter (given preferences for sons). In particular, a 10% increase in median school fees results in a reduction of 2% points (or 5%) in the probability that the migrant worker brings his or her children along, or 0.02 fewer children being brought along. These results especially hold for more vulnerable migrant workers and may be further amplified during an economic crisis.³

1 This number of left-behind children (LBC) is slightly more than the total population of a country, eg., the size of France or the UK. Also note that migrant workers play a major role in the Chinese economy and account for 44% of total urban employment (World Bank and DRC, 2014).

2 For example, parental migration is found to have positive effects on LBC in terms of more education and reduced child labor in Mexico (Alcaraz et al., 2012) and in the Philippines (Yang, 2008), lower infant mortality rates and higher birth weights in Mexico (Hildebrandt et al., 2005), and better cognitive and nutrition outcomes in Nicaragua (Macours and Vakis, 2010). Other studies, on the contrary, found that parental migration has negative effects on child education in Mexico (McKenzie and Rapoport, 2011) and child health in Tonga (Gibson et al., 2011). See Lall et al. (2006) for a detailed survey of internal migration in developing countries and Antman (2013) for a review of the literature on the impacts of migration on family members left behind.

3 These empirical results are obtained using the latest data available from a household survey specially designed for the study of internal migration in China (i.e., the 2008/09 RUMIC data), which we have discussed in more detail in the next section.

School fees take an important role in household education choice. Yet, the existing education literature has mostly focused on the impacts of school fees on enrollment. For example, in the context of China, Yi et al. (2015) found that an unconditional financial aid program (fee-reduction program) had small effects on upper secondary school enrollment for Grade 9 students but no effects for Grade 7 students. Shi (2012) found educational fee reductions to be matched by increased voluntary household educational spending.⁴

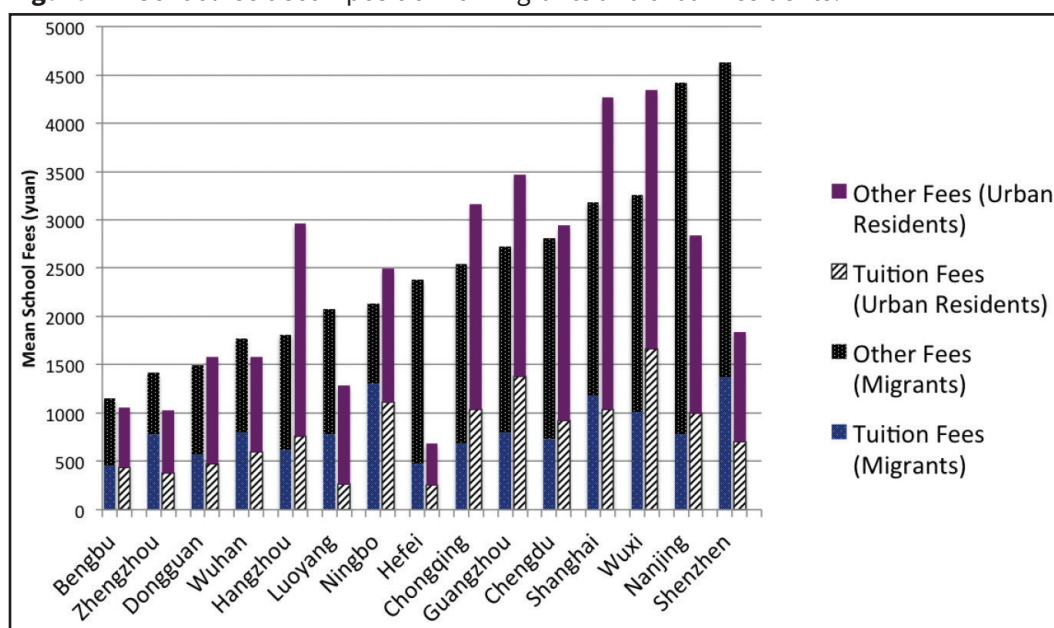
To our knowledge, our paper is among the first studies to straddle two distinct literatures on developing countries: one related to education policies and the other related to internal migration. In this respect, perhaps the closest studies to our empirical analysis are the recent studies by Pan (2017) and de Brauw and Giles (2017), which both focus on educational attainment in rural China when internal migration barriers are relaxed. More specifically, Pan (2017) used an innovative regression discontinuity design approach to study the impacts of a policy change that grants urban residency to a group of rural individuals based on their birth dates. Pan (2017) found that the educational attainments of barely eligible rural residents decreased sharply after the reform, particularly men and those who could permanently migrate to relatively rich areas. Similarly, de Brauw and Giles (2017) showed that migration opportunity leads to lower enrollment for middle school graduates. These results can be explained when the opportunity cost of remaining in the rural school (the returns on migration) becomes greater than the returns on a rural education. Both papers focus on school investments in the area or origin and very little is known regarding the determinants of child migration. Consequently, any new light that is shed on the unique interaction between school fees and the migration decision of children, particularly in the context of a developing country that has been undergoing large-scale rural–urban migration such as China, would be relevant to policy.

We start by providing an overview of the country background in the next section before presenting our analytical framework in Section 3, which discusses the theoretical intuition, the empirical model, and the data. We subsequently discuss estimation results, various robustness checks, and heterogeneity analysis in Section 4. We offer further analysis of health outcomes in Section 5 and conclude in Section 6.

2 Overview of education and school fees

Confucian values that strongly encourage education have historically played a key role in Chinese parents' decision to enroll children in schools. The advent in 1986 of the “Law of Compulsory Education” made school enrollment mandatory for all children aged 6 and older and required all children to attend school for a minimum of 9 years. Grassroot enforcement and monitoring of this law by urban resident committees or rural village councils (the smallest administrative units in China) have helped rank the country among those with the highest

⁴ Recent studies found positive impacts of school fee elimination on enrolment and test scores in other contexts including Colombia (Barrera-Osorio et al., 2007), South Africa (Borkum, 2012), Kenya (Lucas and Mbiti, 2012), and Gambia (Blimpo et al., 2016). For theoretical evidence that increased school fees prevent the poor from having access to better schools, see, e.g., Selod and Zenou (2003). See also Dwenger et al. (2012) and Lange (2013) for recent studies on the effects of tuition fees on the mobility of university students in richer countries' context. See also Dang and Rogers (2008) for a review on studies related to households sending their children to private tutoring (classes with extra fees) and Glewwe and Muralidharan (2016) for a recent review of other studies on education in developing countries. The literature on migration focusing on education issues has highlighted the opportunity of migration to invest or disinvest in human capital (see Stark et al., 1997; McKenzie and Rapoport 2011).

Figure 1 School fee decomposition for migrants and urban residents.

Note: City-level mean school fees of urban residents/migrants are decomposed into two components: (1) tuition fees and (2) other fees (including food and accommodation, remedial classes, uniform and other sponsorship fees, etc.)

Source: Rural–Urban Migration in China 2008.

school enrollment rates. The gross enrollment rate at the primary and secondary school levels reached 103% and 94%, respectively, in 2014 (OECD, 2016).⁵

Universal compulsory education, however, does not fully alleviate the burden of school fees for families. The education system's finance is highly decentralized in China, leading to subnational governments bearing most of the costs of public education spending (approximately 95%) and the central government funding the rest (World Bank and DRC, 2014). These challenges gave rise to school fees as an important source of revenue for local governments' public education budget. These school fees are often collected by the local government (through schools) and then transferred back to each school, with the specific amounts being determined in negotiations between the former and the latter. Notably, migrant households are often asked to pay extra school fees, the exact amounts of which vary from city to city (see, e.g., Yuan, 2010).⁶

No official data exist on school fees, but these can be estimated from household education expenditures. The Rural–Urban Migration in China (RUMiC) data set (discussed in more detail in Section 3.2 and Appendix 2) provides information on household expenditures on various types of school fees faced by migrants and local residents in 15 cities across China. Figure 1 graphs the distribution of mean (total) school fees paid by households in these

⁵ The gross primary (secondary) school enrolment rate is defined as the ratio of children currently enrolled in primary (secondary) school over the number of children in the age groups that should attend primary school; as such, it can be larger than 100% due to, say, repeaters.

⁶ Despite the repeated calls to give migrant children equal treatment, many public schools in China continue to impose higher tuition fees or other fees on migrant children, often with local government approval (World Bank and DRC, 2014). There are at least two main reasons for this. First, compulsory education for migrant children is supposed to be financed by the subnational governments of migrant-sending areas rather than the subnational governments of migrant-receiving areas. The latter lack motivation to finance the education of migrant children and often have inadequate resources to do so, given their already heavy fiscal responsibilities (Shen et al., 2014). Second, subnational governments tend to allocate public resources to activities related to short-term economic performance rather than to local public goods such as compulsory education (Shen et al., 2014; Xu, 2011; Yuan and Zhang, 2015).

15 cities.⁷ For migrant households, the mean school fees range from 1,100 yuan in Bengbu (a city with a dominant food industry in the Northern Anhui province) to more than 4,500 yuan in Shenzhen (the fastest growing migrant receiving city in the South).⁸ School fees as a share of migrant households' consumption range from 4% in Hangzhou to 25% in Shenzhen and represent, on average, 10% of migrant household consumption. For local households (i.e., urban residents with a *hukou*), school fees represent on average 11% of their consumption. School fees can be further broken down into different components, with tuition fees representing 40% and 31% of total school fees for migrants and urban residents, respectively.

There is an inverse relationship between the shares of migrant households who bring school-age children and school fees (Figure 3.2 and the online Appendix 3).⁹ Tuition fees in rural areas were formally abolished by the central government in 2006; thus, the urban school fees paid by migrant households represented additional education expenses to their budget (which they would not have to pay in rural areas). The central government announced the abolition of these fees in urban areas as well after 2008 (State Council, 2008), but in practice, migrant households still often have to pay various "hidden" school fees (Li, 2013; Lu and Zhou, 2013). Indeed, using the RUMiC survey, we found that migrant households received a school fee reduction of approximately 20% in 2009 (refer for the median school fee in Table 3.1 of online Appendix 3).¹⁰ This practice of charging school fees is likely to persist, particularly given the strong fiscal decentralization in the country, unless follow-up policy measures are taken by the central government. We offer the first study that attempts to offer rigorous quantitative evidence on the impacts of school fees on child migration in China; our research is relevant not just as an assessment of the impacts of existing policy practices but also sheds useful light on potential policies accompanying child migration (e.g., whether the government should subsidize child migration to help better integrate migrant households in the city's economy). We return to this discussion in the last section.

3 Analytical framework

3.1 Summary of theoretical model

We provide a more detailed theoretical model with proofs in the working paper version (Dang et al., 2016), which provides guidance for our empirical analysis. We briefly summarize the main results of the model in the following. Our theoretical model considers a two-zone economy with a city and a rural area, and with a rural household that consists of a migrant worker and his (her) child(ren). The worker must decide among three choices: (i) migrating alone to the city, (ii) migrating to the city with the child, or (iii) remaining in the rural area with the child.

⁷ We consider the mean school fees here to facilitate comparison of the fee structure, including tuition fees and other fees. See Figure 3.1 in the online Appendix 3 for a graph that shows the median school fees separately for urban and migrant households. The online Appendix 3 is available at the following link: https://huangyang.weebly.com/uploads/1/5/1/5/15150676/dhs_-_children_left_behind_in_china_-_online_appendix_3.pdf.

⁸ Unless stated otherwise, school fees are calculated from the sample of migrant households with children enrolled in a school in the city. One yuan was approximately equal to 0.14 US dollars in 2008 (World Bank, 2016).

⁹ The correlation between the shares of migrant households who bring school-age children and city-level median school fees is -0.28 . We return to a more detailed description of the way we construct different measures of school fees in Section 4.2.

¹⁰ Our estimates using the most recent household survey from China in 2012 (i.e., the China Family Panel Studies implemented by Peking University) also indicate that, 4–6 years after the official abolition of school fees in urban (rural) areas, both urban and rural households still paid various school-related fees (results are available upon request).

The city offers better labor market outcomes and better schooling outcomes than the rural area, but the worker has to pay a migration cost to migrate to the city.¹¹ We assume that the worker has a general additive linear utility function that consists of household disposable income and his child(ren)'s schooling and non-schooling outcomes.

When deciding whether to migrate and whether to take his child with him, the worker compares his gain in utilities in the three choices described earlier. Our theoretical model predicts that higher school fees decrease the probability that a migrant worker brings his children with him to the city, the number of children he may bring, and the probability that he brings a daughter given possible preference for boys over girls (or given gender-differentiated returns on education in the labor market). These effects may be more pronounced for more vulnerable migrant workers and during an economic crisis (when returns to education are low). Our framework also implies that, other things equal, the migrant worker is also more likely to bring his children along if he values non-schooling outcomes obtained in the urban area. Our framework is also compatible with a scenario where, faced with high urban school fees, the migrant worker decides to leave one or several children in the rural area and to send remittances to support these children. We discuss the estimation models in the next subsection.

3.2 Empirical model

We estimate the migrant worker's decision to bring his children along using the following province (of origin) fixed-effects model:

$$Y_{ikj} = \delta + \lambda Fee_{ikj} + \theta' Z_{ikj} + \mu_j + \varepsilon_{ikj} \quad (1)$$

where Y_{ikj} is a dummy variable indicating whether the migrant worker (or the head) in household i in city k originating from province (region) j brings his children along and Fee_{ikj} is the school fees (in natural logarithm) faced by household i . We expect the coefficient on school fees (λ) to be negative (which is consistent with the theoretical intuition that a higher school fee induces the worker not to bring his children). The control variables Z_{ikj} represent the household head's characteristics such as age, gender, educational achievement, working status, original residence, and destination city-level characteristics including the growth rate of the student–teacher ratio and housing prices. The region-of-origin fixed effects μ_j helps control for unobserved characteristics commonly affecting the migrant workers who originate from the same region j (e.g., if living expenses are systematically lower in this region).¹² We estimate

11 For a version with more than one city, see the more complex version developed in the working paper (Dang et al. 2016). For simplicity and without any loss of generality, we assume that the migration cost is not a function of the number of household members who migrate.

12 Provinces with few out-migrants are collapsed with their neighboring provinces into regional dummy variables (e.g., in our estimation sample, because Gansu has six migrants, Qinghai three migrants, Shaanxi 12 migrants, and Xinjiang one migrant, we created a northwestern province dummy for these four provinces). In the end, we constructed eight regional dummy variables: central province (Chongqing, Henan, Hubei, Hunan, Sichuan), eastern province (Jiangsu, Shanghai), northwestern province (Gansu, Qinghai, Shaanxi, Xinjiang), northern province (Shandong, Hebei, Tianjin), northeastern province (Heilongjiang, Jilin, Liaoning), south central province (Anhui, Jiangxi), southeastern province (Guangdong, Fujian, Zhejiang), and southwestern province (Guangxi, Guizhou, Yunnan). We also offer estimates that use the province of destination fixed effects (Table 3.3 in the online Appendix 3), which show qualitatively similar results.

Equation (1) using a linear probability model for easier interpretation of the coefficients.¹³ We provide robust standard errors that are clustered at the city level for all the regressions. As suggested by Cameron and Miller (2015), however, we also provide robustness checks using wild bootstrap robust standard errors.

School fees, however, may be prone to measurement errors or be potentially correlated with some unobserved city-level characteristics that also affect the migrant worker's decision to bring his children. There may even be reverse causality if, say, the influx of migrant children turns out to exceed the capacity of schools in the city; in this case, the city government may raise fees to obtain more revenue. Because our theoretical intuition suggests that a higher school fee has a negative impact on the migrant worker's decision to bring his children, these endogeneity issues would bias estimates upward toward zero. But the magnitude of this upward bias is clearly an empirical issue.

Therefore, we use an instrumental variable (IV) framework to identify the impacts of school fees and jointly estimate Equation (1) and the following first-stage equation for the year 2007

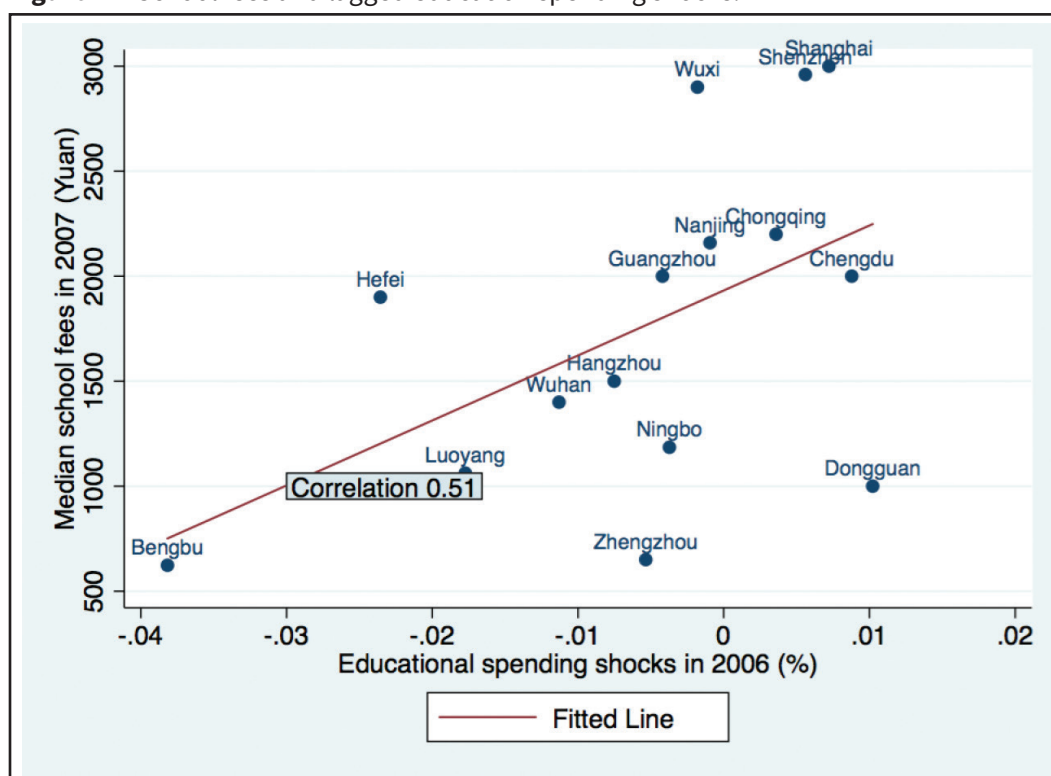
$$Fee_{ik, 2007} = \tau + \omega Shock_{ik, 2006} + \phi' Z_{ik} + v_j + \eta_{ik} \quad (2)$$

where the instrumental variable $Shock_{k, 2006}$ is the lagged cyclical component of the city's public education spending in 2006 (i.e., obtained after detrending city education spending from 2002 to 2006). This IV satisfies all the conditions of a good IV, that is relevance, exogeneity, and exclusion conditions. We start first with discussing the relevance condition.

As discussed earlier, the funding of the Chinese education system is strongly decentralized. Households are required to pay tuition and miscellaneous fees to supplement school operating expenses, and these fees are set by the local governments and schools. Although the Education Law stipulates that public education spending should grow faster than regular government revenues, in practice, local governments are not held accountable to meet specific spending targets. This leaves local governments the flexibility to make up for the shortfall in public spending with contributions from households. A recent study by Yuan and Zhang (2015) found that increases in public education spending are associated with significant decreases in urban household spending on public school tuition. This situation is particularly relevant to migrant households, for whom the negative association between local public education spending and school fees is likely to be stronger. Since the funding of school does not follow migration (World Bank and DRC, 2014), the education of migrant children is only partially funded by the local government in the destination area. Migrant children are required to pay extra fees on top of the regular fees; furthermore, these fees are less regulated than tuition fees and may be adjusted according to school needs.

Figure 2 plots city-level median school fees against public education spending shocks (which range from -3.8% to 1% as a share of the city's public spending). To remove contemporaneous issues, we use 1-year lagged shocks rather than the current shocks as an instrumental variable (i.e., the fees are in 2007 but the spending shocks are in 2006). There is a clear positive relationship between school fees and lagged education spending shocks (with a correlation coefficient of 0.51). A natural explanation is that if the local government overspent in

¹³ Estimates using a probit model are similar and shown in the online Appendix 3.

Figure 2 School fees and lagged education spending shocks.

Note: We plot the median school fees paid by migrants in 2007 against the city-level education spending shocks in 2006 (linear filter).

Sources: Rural–Urban Migration in China 2008 and China City Statistical Yearbook 2002–2008.

the previous year, they tend to compensate for the current fiscal deficit by raising current-year school fees.¹⁴

We now turn to discuss why the cyclical components of public education spending shocks are exogenous to the migrant households' decision to bring their children and why these shocks only affect this decision through school fees. In China, households, and particularly migrant workers, have little power to influence local governments' decisions. Local budgeting is largely influenced by a few top local officials and does not involve local residents (Wang et al., 2012; Liu et al., 2015). Because these officials are appointed, evaluated, and promoted mostly based on local economic performance and tax revenues, they have strong incentives to allocate public resources to activities directly oriented toward these objectives, rather than to the provision of local public good—such as education—that would meet the needs of local residents (Xu, 2011). A recent study (Tsai, 2016) also suggests that local public spending responds to political cycles, which are completely exogenous to the migrant workers' decision.¹⁵ In addition, public

¹⁴ The City Statistical Yearbooks, unfortunately, do not offer public education spending data that are disaggregated by compulsory school levels (grades 1 to 9) and non-compulsory school levels (grades 10 to 12). This may weaken the strength of our instrumental variable (IV); but on the other hand, it also offers more robust estimates since we examine aggregate shocks to all education levels. Also note that due to mean reversion, our positive correlation between current school fees and lagged education spending shocks is consistent with Yuan and Zhang's (2015) negative correlation found for current school fees and current education spending shocks. In other contexts, including the European Union, public spending shocks are found to result in budget deficits (Beetsma and Giuliodri, 2011); see also Ramey (2011) for a recent review of related studies. We also obtain a similar result when pooling both the 2007 and 2008 survey rounds of the RUMiC and control for city-level fixed effects in robustness checks (see Table 3.16 of the online Appendix 3).

¹⁵ Tsai (2016) showed that two years prior to the National Congress of the Communist Party, politicians were likely to shift public spending toward capital expenditures, such as innovation funds and capital construction, and away from current expenditures, such as agricultural subsidies, social expenditures, and government administration.

education spending has traditionally been invisible to migrants—as local budgeting was not publicly disclosed until recently—and migrants are often neither interested in nor informed about local public affairs. Furthermore, even if we assumed that migrants could somehow predict the trend of local public education spending, the shocks to education spending would remain unexpected and unforeseeable. It thus seems reasonable to consider these shocks as exogenous in our empirical setting.

As for the exclusion restriction, the most viable mechanism through which shocks to public education spending could affect the migrant workers' decision to bring their children is increased school fees. As discussed earlier, the budgeting process appears so far removed from migrant households (and local households) that it is unlikely to affect these households directly. Moreover, even if we generously allowed the 1-year lagged shocks to education spending to affect other city-level characteristics that are directly related to the migrant households' decision—an example could be that the education budget surplus may lead to the recruitment of more teachers or the construction of new schools—such scenarios are typically multi-year projects. They would take much longer than the IV's short time span of 1 year to develop. Furthermore, in the context of China, information about these projects may even take longer to percolate to migrant households and subsequently affect their decision.¹⁶

Still, it could be argued that if unexpected shocks to public education spending are somehow correlated with other types of social welfare spending such as spending on health or security and if such social welfare spending can help improve the non-schooling outcomes for migrant workers' children, these shocks may also affect child migration through this channel. This would result in biased estimates. This argument, however, is unlikely to hold since, as discussed earlier, migrant households are generally granted limited access to social services in urban areas. Consequently, increases (or decreases) in other types of public spending would likely have little effect on their decision over child migration. The area of health care furnishes a good illustration. In 2006, only 28% of the urban population was covered in the government basic urban healthcare insurance scheme, which does not cover migrant workers (Hu et al., 2008). Furthermore, migrant workers tend to underuse health services in their destination cities, as almost two-thirds of migrant workers who report illness do not visit a doctor (Gong et al., 2012). Another type of public spending—social protection spending—provides similar evidence.¹⁷ In our data, it is also noticeable that the correlation between social protection spending and public education spending shocks is almost zero anyway (i.e., -0.06).

Yet, another potential channel through which the exclusion restriction can be violated is if unexpected shocks to public education spending are correlated with other (unobserved) macroeconomic shocks, which in turn would affect migrant workers' employment and their decision to bring their children. However, this critique is not directly relevant to our study since we focus our analysis on the sample of migrant workers who remain in the city, rather than on all workers who have ever migrated to the city (and may have subsequently left).¹⁸

¹⁶ We also control for the growth rate of student–teacher ratio in Equations (7) and (8).

¹⁷ Social protection spending is defined in the China City Statistical Yearbooks as being composed of social security benefits, employment subsidies, and unemployment grants. Migrant workers generally have no access to other social welfare benefits—which are closely tied with residence status—such as social security, housing, transportation, and medical benefits (Wang and Zuo, 1999; Wong et al., 2007; Song et al., 2008; World Bank and DRC, 2014).

¹⁸ Furthermore, analyzing the population of ever-migrant workers would require very detailed longitudinal data that track their residences and decisions over time, which are not available.

Nevertheless, we use two different strategies to provide additional layers of robustness checks on the exclusion restriction. First, we use different model specifications that control for a number of variables in estimating Equations (1) and (2). These include the migrant worker's (household head's) demographics, employment, and dummy variables indicating his work industry, province of origin, and whether he migrates within the same province. If somehow there is a reason to believe that the city-level shocks to public education spending can have differential effects on different occupations and migrant workers coming from different locations, these variables can help net out such effects. Furthermore, we explicitly control for social protection spending in a robustness check. If the estimated coefficient on school fees does not lose its statistical significance (or change significantly) when social protection spending is included, this would provide supportive evidence for the validity of the exclusion restriction. We also control for the province-level consumer price index (CPI) in another robustness check, which can offer further evidence on potential impacts of unobserved macroeconomic shocks on migrant workers' employment prospects and income.

Second, we apply a bounding method recently developed by Chernozhukov et al. (2013) that does not require the exclusion restriction. This second strategy, in fact, generally allows for the violation of the exclusion restriction to occur due to any reason. We describe this method and our implementation in more detail in Appendix 1.

3.3 Data description and construction of variables

We bring together various data sources for the empirical analysis. Our main data set is the RUMiC survey, which consists of three independent modules: a migrant household module, an urban household module, and a rural household module. It collects rich data on the socio-economic characteristics of rural–urban migrants and their LBC, including information on co-residence status, schooling status, and household expenditures on various types of school fees for their children. We restrict our sample to households that have at least one school-age child (age 6–16 years) as we focus on the impacts of school fees on child migration. This leaves us with a working sample of 1,349 households. Almost all (97%) of the children in the migrant households are enrolled in school (at the primary and junior high school levels), and they are evenly distributed from grade 1 to grade 9. The majority (more than 90%) of these children attend public school. The number of children, as well as the number of daughters, is similar for migrant households who bring their children to the cities and for those who do not do so. We provide a more detailed description of this survey and other data sources in Appendix 2.

While we analyze two rounds of the RUMiC data set, we focus in this paper on the 2008 (first) round for two main reasons. First, as discussed earlier, local governments typically relied on raising revenues through school fees before 2008 to compensate for the lack of funding transfer from the central government to pay for the education of migrant children. The abolition of school fees in 2008 resulted in local governments being no longer able to collect revenues this way, at least in theory. Thus, there could be (almost) no correlation between school fees and budget deficits, which violates the relevance condition of our IV for 2009. Second, the linkage between shocks to public education spending and school fees is also likely to be weakened during an economic crisis. This is because local governments would typically be constrained by competing spending priorities in such times, thus would unlikely have total

discretion over their education budget. For example, they might not be able to spend the surplus from the education budget generated in the previous year on education in the following year, which prevents them from lowering school fees.¹⁹ Our use of the 2009 round will thus be limited to supplementary analysis.

Administrative data on city-level school fees are rarely, if at all, available for China (and other developing countries). As such, we compute the city-level median of migrant households' per migrant child expenditures on all school-related fees as the city-level measures of the school fees faced by migrant households.²⁰ To reduce endogeneity concerns with school fees, we exclude each household before implementing this calculation (i.e., for each migrant household, the median is based on the expenditures of all the migrant households in the sample except theirs). For robustness checks, in addition to the median, we also compute alternative measures such as the 25th percentile, the 75th percentile, and the mean of the household education expenditures.

As another check, we also compute alternative measures of school fees based on urban residents' school expenditures in the same cities. Indeed, Figure 1 reassuringly indicates that there is no systematic difference between school fees obtained from the rural household sample or the urban household sample. Consequently, the school fees that urban households pay can be viewed as an alternative measure of school fees in the city (e.g., because of a different sampling frame for the urban households in the same city).²¹ Thus, while the fees obtained from the migrant household sample can vary for each migrant household, the fees obtained from the urban household sample are, by construction, the same for all migrant households in a given city. The latter measure is further removed from any concern with the endogeneity of school fees, since these fees represent what each migrant household is (exogenously) faced with when migrating to the city. There is also a strong correlation between the two measures, which is 0.74.

To further check that our constructed variable for the school fees is robust to different (observed and unobserved) city and household characteristics—particularly student age—we explicitly model school fees as a function of these characteristics and provide estimation results based on this predicted variable. In particular, we regress the city-level median school fees on these characteristics as follows:

$$Fee_k = \delta + \theta' Z_i + \lambda age_i + f_k + \varepsilon_{ik} \quad (3)$$

We subsequently use the estimated parameters from Equation (3) to predict school fees at the household level and use the predicted school fees \widehat{Fee}_{ik}^1 as our measures of school fees:

$$\widehat{Fee}_{ik}^1 = \hat{\delta} + \hat{\theta}' Z_i + \hat{\lambda} age_i + \hat{f}_k \quad (4)$$

19 We do not explore the panel feature of the data set between 2008 and 2009 since despite substantial efforts to track individuals over time, the panel data suffer from exceptionally heavy attrition (58.4%). This is due to the mobile nature of migrant workers and the consequences of the financial crisis that hit China in 2009 (Akgüç et al., 2014). However, we also show estimation results later when we pool the 2 years and use a city fixed-effects model. An option is to construct synthetic panel data that can allow dynamic analysis (Dang et al., 2014), but we leave this for future research.

20 These fees include tuition, food and accommodation, remedial classes, other fees (e.g., school uniforms and so on) and "sponsorship fees/boarding fees/selecting school fees". Unless otherwise noted, all numbers are our estimates from the RUMiC survey.

21 The school fees that urban households pay may be very different from those paid by migrant households if there is school selection by urban households, but the results in Figure 1 rule out this hypothesis. See also Carletto et al. (2014) for a detailed discussion on the construction of proper sampling frames for collecting migration data.

Yet, these school fee measures may still be endogenous at the city level if unobserved city-level events occur that affect both a city's school fees and its migrant workers' decisions regarding child migration. As discussed earlier in the presentation of the empirical model, we address this issue by instrumenting school fees with the one-year lag of unexpected shocks to the city government's education spending. We gathered the historical city-level education spending as a share of local public spending in the 15 cities (metropolitan areas) covered by RUMiC 2008 for the period 2002–2007 from the China City Statistical Yearbooks. For each city, using different detrending techniques (i.e., Hodrick–Prescott (HP) filter and linear filter), we decomposed the time series records into a trend component and a cyclical component.

We constructed a measure for the trend in city education services with the growth rate of the student–teacher ratio in 2007 based on the number of students and teachers in metropolitan areas in 2006 and in 2007 using the China City Statistical Yearbooks. As a proxy for migration distance between the original and the destination areas, we constructed a dummy variable that equals 1 if the migrant household is from a rural area within the same province and equals 0 if the migrant household is from another province. Since city-level CPI data are not available for China, we proxy for living costs with city-level housing prices in 2007 from the China Urban Life and Price Yearbook 2008.

Table 1 shows the summary statistics for household and city characteristics. The average age of household heads in our sample is 36.7, with approximately one-fourth (26%) of households being headed by females. About half of all household heads are primary school graduates, and less than one-third (29%) of them hold a junior high school diploma or higher. In all, 38% of migrant households bring their children with them to the city, and a migrant household has on average 0.46 migrant children; out of these households, 7% bring two children or more, and less than half (43%) of the migrant children are girls (not shown). About two-thirds of migrant households have both spouses living together, and more than half (57%) of the migrant households are from the same province (suggesting that within-province, migration costs are lower). About half (47%) of the migrant households currently live in cities in coastal provinces (hereafter referred to as coastal cities for short). Almost all (97%) household heads are employed, and slightly more than one-third (36%) of all household heads are self-employed. Only one-third of all household heads have a long-term work contract. The average annual education remittance sent back home by migrant households in 2007 was 1,100 yuan, amounting to about 5% of a migrant household's annual income. Overall, the student–teacher ratio in 2007 did not change much compared with that in 2006, even though the change was larger (up to 7%) in some cities. Lastly, the average housing price in 2007 was about 5,600 yuan per square meter in these 15 cities, with the price in the most expensive city being about six times greater than that in the least expensive city.²²

4 Impacts of school fees

4.1 Estimation results

We use three model specifications to estimate Equation (1) (and Equation (2)) for both comparison purposes and robustness checks. Specification 1 is the most parsimonious and only

²² The sample for the 2009 round is somewhat different from that for the 2008 round. For example, households are less likely to bring their children to the city but have slightly more income per capita and more household heads are female (not shown).

Table 1 Summary statistics from the RUMiC sample, China 2008

Variable	(1)	(2)	(3)	(4)	(5)
	n	Mean	SD	Max	Min
Household characteristics					
Head's age	1,349	36.77	4.99	62	20
Head is female	1,349	0.26	0.44	1	0
Head completed primary school	1,349	0.82	0.39	1	0
Head completed middle school	1,349	0.29	0.46	1	0
Head lives with spouse	1,349	0.65	0.48	1	0
Head lives with child	1,349	0.38	0.49	1	0
Number of school-age children living with head	1,349	0.46	0.65	3	0
Migrated within province	1,349	0.57	0.50	1	0
Remittances sent out for educational purposes ('000 yuan)	1,349	1.10	2.23	18	0
Household per capita income ('000 yuan)	1,349	1.34	1.01	12	0
Head is working	1,349	0.97	0.16	1	0
Head is self-employed	1,349	0.36	0.48	1	0
Destination city characteristics					
Growth rate of student–teacher ratio	1,349	1.02	2.19	6.56	−2.58
Education spending shocks (HP filter, lagged 1 year)	1,349	−0.29	0.93	1.05	−2.66
Education spending shocks (linear filter, lagged 1 year)	1,349	−0.46	1.27	1.02	−3.82
Education spending shocks (HP filter, lagged 2 years)	1,349	−0.64	0.96	0.39	−3.50
Housing prices in 2007 ('000 yuan)	1,349	5.60	2.62	13.37	2.29
Mean school fees (in migrant sample) (Ln)	1,349	2475.05	887.85	5720.00	954.17
Median school fees (in migrant sample) (Ln)	1,349	1758.46	699.62	3130.00	650.00
Coastal city	1,349	0.47	0.50	1	0
Guangzhou	1,349	0.07	0.25	1	0
Dongguan	1,349	0.05	0.22	1	0
Shenzhen	1,349	0.04	0.19	1	0
Shanghai	1,349	0.11	0.31	1	0
Nanjing	1,349	0.06	0.24	1	0
Wuxi	1,349	0.03	0.16	1	0
Hangzhou	1,349	0.08	0.27	1	0
Ningbo	1,349	0.04	0.20	1	0
Zhengzhou	1,349	0.07	0.26	1	0
Luoyang	1,349	0.04	0.19	1	0
Hefei	1,349	0.09	0.29	1	0
Bengbu	1,349	0.06	0.23	1	0
Chongqing	1,349	0.09	0.29	1	0
Wuhan	1,349	0.08	0.27	1	0
Chengdu	1,349	0.10	0.30	1	0

RUMiC, Rural–Urban Migration in China; SD, standard deviation; Max, maximum; Min, minimum; HP, Hodrick–Prescott.

Sources: RUMiC 2008 and China City Statistical Yearbook 2002–2008.

controls for the household head's characteristics (including age, gender, educational achievement). Specification 2 adds to Specification 1 the head's employment characteristics (including whether the head is working and whether the head is self-employed), a dummy variable indicating whether the head migrated within the same province, as well as dummy variables indicating the industry the head works in.²³ Finally, Specification 3 adds to Specification 2 the city-level housing prices to proxy for living costs in the city. We estimated these three specifications using median school fees (with fees measured on the natural logarithm scale).²⁴

While the variables further added to Specification 1 can help increase the goodness-of-fit of the model, they are more likely to be endogenous to the migrant worker's decision (e.g., the migrant worker may decide to be self-employed or to migrate within the same province to take better care of his or her children). However, if the estimation results are (qualitatively) similar for all three specifications, it would provide stronger evidence for the impacts of school fees. For this reason, although Specification 3 is our preferred specification, we also refer to the other specifications when interpreting the estimation results.

We provide in Table 2 the estimation results for Equations (1) and (2) using the linear probability model, where the non-IV estimates are shown at the bottom of the table to save space. These estimates for Specifications 1 and 2 using the median school fees (Table 2, columns 1 and 2) point to a negative and statistically significant relationship between school fees and the migrant worker's decision to bring his or her children. Adding housing prices to the regression (column 3) renders this relationship statistically insignificant but does not change the negative sign. However, as discussed earlier, the non-IV estimates mask the true impacts of school fees since they are biased upward toward zero. Put differently, they should be considered as the lower bound estimates in absolute magnitude of the true impacts.

We then instrument school fees with the shocks to local governments' education spending and show the full estimation results in the upper part of Table 2.²⁵ The lowest value of the (Kleibergen-Paap) F statistics (from the first-stage regression) is 8.3 (column 1) and is somewhat lower than the rule of thumb ($F > 10$) suggested by Stock and Yogo (2005); however, all the other F statistics are above this threshold, suggesting that our instrument is a reasonably good instrument.²⁶

All the estimated coefficients on the school fees variables are still negative and now statistically significant at the 5% level or less. Furthermore, these coefficients are between two and three times larger in absolute magnitude than those from the non-IV regressions. This confirms the negative impacts of school fees on migrant workers' decisions to bring their children along—as predicted by our theoretical intuition—and supports our expectation that the non-IV estimates are biased upward toward zero. Since school fees are in natural logarithm, for small changes in school fees, the magnitude of the impacts (semi-elasticity) can be read directly from the estimated

23 We control for four industry dummy variables for the following sectors: manufacturing, construction, wholesale and retail trade, and hotel and catering services (with an "others" sector as the reference category). These four sectors absorb about 80% of the migrants. We do not control for the head's income because of potential endogeneity issues (e.g., as households may jointly decide on the type of job they do and thus on the pay they get and whether to bring their children along). We will return to this issue later in the section on robustness checks.

24 As a robustness check, we also run all our regressions with mean instead of median school fees (see Table 3.3 of the online Appendix 3). The regressions using median fees, however, are our preferred specifications, since the median is likely less affected by outlier observations than the mean.

25 The first-stage regression results are reported in Table 3.4 of the online Appendix 3, for both the median and the mean school fees.

26 Note that Stock and Yogo's rule of thumb applies to identically and independently distributed errors, whereas our estimates are obtained with robust standard errors. Our IV also passes the Anderson–Rubin test for weak-instruments (not shown), which is valid with robust standard errors.

Table 2 Effects of median school fees on child migration, China 2008

Variable	(1)	(2)	(3)
Median school fee (Ln)	-0.428** (0.169)	-0.168*** (0.057)	-0.160** (0.068)
Head's age	0.004 (0.004)	0.004 (0.003)	0.004 (0.003)
Head is female	0.092 (0.058)	0.025 (0.045)	0.025 (0.045)
Head completed primary school	0.013 (0.036)	-0.013 (0.030)	-0.012 (0.029)
Head completed middle school	0.009 (0.028)	0.024 (0.028)	0.023 (0.027)
Head is working		-0.115** (0.057)	-0.112* (0.060)
Head is self-employed		0.281*** (0.032)	0.279*** (0.033)
Migrated within province		0.133*** (0.048)	0.123*** (0.038)
Growth rate of student-teacher ratio		-0.014** (0.007)	-0.013 (0.008)
Housing price in 2007 ('000 yuan)			-0.004 (0.008)
Constant	3.413*** (1.233)	1.500*** (0.406)	1.467*** (0.464)
Observations	1,349	1,349	1,349
Mean of dependent variable	0.378	0.378	0.378
Original province FE	Yes	Yes	Yes
Industry FE	No	Yes	Yes
RMSE	0.493	0.432	0.432
Prob > χ^2	0.000	0.000	0.000
First-stage <i>F</i> statistics	8.273	21.165	15.146
Non-instrumented regressions	-0.141** (0.062)	-0.072** (0.034)	-0.042 (0.042)

Notes: Each column presents the results from separate IV regressions with different independent variables, where the IV is the one-year lag of shocks to public education spending. The dependent variable is a dummy variable that equals 1 if there is at least one child living with the household head and 0 otherwise. The regressions use the median school fees reported in the migrant household sample as a regressor. Different sets of control variables are included in different columns. *R*-squared values are not reported, instead RMSE, the sample standard deviation of the differences between the predicted values and observed values, is reported under each column. Standard errors in parentheses are clustered at the city level. Prob > χ^2 is the *p*-value of the chi-square test of overall significance. *F* statistics of the first-stage regressions are also reported. ****p* < 0.01, ***p* < 0.05, and **p* < 0.1. FE, fixed effects; RMSE, root mean square error; RUMiC, Rural-Urban Migration in China.

Sources: RUMiC 2008 and China City Statistical Yearbook 2002–2008.

coefficients. A 10% increase in school fees results in approximately between a 2% point decrease (Table 2, column 3) and a 4% point decrease (column 1) in the probability that the migrant worker brings his or her children along.²⁷ Given that 38% of migrant households bring their children with them to the city, these figures are equivalent to a 5% (=2/38) and 11% decrease, respectively, in the probability that the migrant worker brings his or her children along.

Estimation results for the other control variables (columns 2 and 3) show the expected impacts on the migrant worker's decisions. In particular, if the migrant worker is self-employed

²⁷ An alternative interpretation is to estimate and plot the predicted probabilities at different levels of school fees; see Figure 3.3 of the online Appendix 3 for this approach.

Table 3 Effects of median school fees on the numbers of children brought to the city, China 2008

Variable	(1)	(2)	(3)
Median school fee (Ln)	-0.536** (0.227)	-0.211** (0.089)	-0.205** (0.103)
Observations	1,349	1,349	1,349
Mean of dependent variable	0.458	0.458	0.458
HH's employment variables and industry FE	No	Yes	Yes
Growth rate of student-teacher ratio	No	Yes	Yes
Housing prices in 2007	No	No	Yes
RMSE	0.493	0.432	0.432
Prob > χ^2	0.000	0.000	0.000
First-stage <i>F</i> statistics	8.273	21.165	15.146

Notes: Each column presents the results from separate IV regressions with different independent variables, where the IV is the 1-year lag of shocks to public education spending. The dependent variable is the numbers of children living with their parents in the household. The regressions use the median school fees reported in the migrant household sample as a regressor. Similar to Table 2, household head's demographics and original province FE are controlled in all the columns, and additional sets of control variables are included in columns 2 and 3. *R*-squared values are not reported. Instead, RMSE, the sample standard deviation of the differences between the predicted values and observed values, is reported under each column. Standard errors in parentheses are clustered at the city level. Prob > χ^2 is the *p*-value of the chi-square test of overall significance. *F* statistics of the first-stage regressions are also reported. ***p* < 0.05, FE, fixed effects; HH, household; RMSE, root mean square error; RUMiC, Rural-Urban Migration in China.

Sources: RUMiC 2008 and China City Statistical Yearbook 2002–2008.

or has migrated to a city within his or her original province, he or she is more likely to bring his or her children along. The first result may be explained by the fact that self-employment may give the migrant worker a more flexible work schedule that permits better care of children; the second result suggests that within-province migration may provide migrant children with better prospects, perhaps because of either lower migration costs or similar languages or cultural proximity. The growth rate of the student-teacher ratio has a negative effect on the migrant worker's decision, but this result is not strongly statistically significant.

Table 3 shows the impacts of school fees on the number of children the migrant worker brings to the city. The estimated coefficients on school fees are negative and strongly statistically significant, except for column (2) where the effect is only significant at the 10% level. A 10% increase in the median school fees (Table 3, column 3) would lead to 0.02 fewer children being brought along. Other coefficients largely remain in the same order of magnitude as those in Table 2 (not shown).²⁸

We then examine whether school fees result in gender discrimination against girls. Put differently, we want to know if, conditional on having at least one school-age girl, the migrant workers bring their sons instead of their daughters in response to higher school fees. For each migrant household having at least one daughter, we define a variable indicating girl

²⁸ We ran the same regressions with mean school fees, which provide qualitatively similar results (see Table 3.5 of the online Appendix 3).

Table 4 Effects of median school fees on the gender of children brought to the city, China 2008

Variable	(1)	(2)	(3)
Median school fee (Ln)	-0.417 (0.234)*	-0.086 (0.085)	-0.082 (0.096)
Observations	662	662	662
Mean of dependent variable	0.377	0.377	0.377
HH's employment variables and industry FE	No	Yes	Yes
Growth rate of student-teacher ratio	No	Yes	Yes
Housing prices in 2007	No	No	Yes
RMSE	0.491	0.420	0.420
Prob > χ^2	0.040	0.000	0.000
First-stage <i>F</i> statistics	6.926	19.696	12.374

Notes: Each column presents the results from separate IV regressions with different school fee measures and different independent variables, where the IV is the 1-year lag of shocks to public education spending. The dependent variable is *girl representativeness* – defined as girls as a share of the number of migrant children divided by girls as a share of the total number of children in the household. Regressions use the median school fees reported in the migrant household sample as a regressor. Similar to Table 2, household head's demographics and original province FE are controlled in all the columns, and additional sets of control variables are included in columns 2 and 3. *R*-squared values are not reported, instead RMSE, the sample standard deviation of the differences between the predicted values and observed values, is reported under each column. Standard errors in parentheses are clustered at the city level. Prob > χ^2 is the *p*-value of the chi-square test of overall significance. *F* statistics of the first stage regressions are also reported. **p* < 0.1. FE, fixed effects; HH, household; RMSE, root mean square error; RUMiC, Rural-Urban Migration in China.

Sources: RUMiC 2008 and China City Statistical Yearbook 2002–2008.

“representativeness”, which is the share of girls in the number of children brought along over the share of girls in the household's total number of children. If this variable is larger (smaller) than 1, then girls are “over-presented” (“under-represented”) as migrants. Estimation results restricted to the sample of migrants that have at least one daughter are shown in Table 4.

All the estimated coefficients on school fees are negative but only marginally statistically significant at the 10% level under column (1). This result can thus provide some supportive, but not very strong, evidence for girl discrimination when school fees are higher. However, note that the weak significance may also result from the smaller sample size—which is less than half of that in Tables 2 and 3—when we restrict the estimation sample to migrant households with at least one school-age girl. The empirical estimation results in Tables 3 and 4 are thus consistent with the theoretical intuition.²⁹

As an addition check on gender discrimination, we provide estimates for three different samples. The first sample consists of at least one daughter and one son (sample 1), the second sample consists of households with only one daughter (sample 2), and the third sample consists of households with only one son (sample 3). Estimation results (shown in Table 3.7 of the online Appendix 3) also point to some slightly stronger and more negative impacts of school fees on the probability of bringing girls to the city. For example, the estimated coefficient on this probability

²⁹ We ran the same regressions with mean school fees (see Table 3.6 of the online Appendix 3).

is -0.27 for sample 1, while it is -0.22 for sample 2. However, these coefficients are not statistically significantly different from each other. There is a qualitatively similar result with sample 3 and sample 4, where the estimated coefficient for the probability of bringing the only daughter to the city is -0.22 , while the corresponding figure for the probability of bringing the only son to the city is -0.21 . However, these two coefficients are not statistically significantly different from each other.

4.2 Robustness checks

Our estimation results remain stable against different robustness checks. All the robustness checks in Table 5 remain statistically significant. We discuss next the specific checks.

4.2.1 Alternative measures of school fees

To rule out the concerns that our results may be driven by how the school fee variable is defined, we examine below four different options to construct this variable and present the estimation results in Table 5. For comparison purposes, we show the same estimates from column 3 of Table 2 in column 1 of this table. First, instead of looking at total school fees (which consists of tuition fee, food and accommodation, remedial class, and other fees), we focus on its major component—the tuition fee.³⁰ Estimation results (Table 5, column 2) are qualitatively similar to those under column 1, even though they are unsurprisingly slightly smaller in magnitude.

Second, to allay the concern that the median fees may not be the best measure, we consider other measures such as the 25th and the 75th percentiles of the distribution of school expenses. These percentiles provide further checks against the possibility that outliers may possibly dominate the distribution of school fees and affect the results. Estimates shown under columns 3 and 4 are qualitatively similar to those under column 1, and are even slightly larger in magnitude.³¹ Third, instead of converting the school fees into logarithmic form, we consider them in units of thousand yuan. Estimation results shown under column 5 are, again, qualitatively similar. Finally, instead of using the fees paid by migrant households, we use the fees paid by urban households in the same city. As discussed earlier, the school fees that they pay can offer another measure of the distribution of school fees in the city. We show estimates for both the median total fees (column 6) and the median tuition fees (column 7), which are qualitatively similar even though smaller in magnitudes.³² Finally, we provide estimation results using the predicted school fees based on Equations (3) and (4) in Table 3.10 of the online Appendix 3. Estimation results are qualitatively similar.³³

³⁰ Note that schools uniformly charge tuition fees across the country, whereas the use of other fees may vary from city to city.

³¹ We also consider other percentiles of the distribution of school expenses such as the 10th, 15th, 85th, and 90th, but estimates are qualitatively similar; see Table 3.8 of the online Appendix 3. We also include in this table the province-level CPI 2007 to further control for living cost differences among the cities.

³² We ran the same regressions with mean school fees, which provide qualitatively similar results (see the Table 3.9 of the online Appendix 3). For a further robustness check, we generated a new variable for the difference between the median school fees for migrant children and the tuition fees for urban children. The estimated coefficient on this variable is still negative and strongly statistically significant (not shown).

³³ As a further check on whether school fees may influence migrant workers' decision to bring young children versus older children, we constructed a variable that measures the representativeness of young children (children of primary school age or 6–12 years old). This is defined as young children as a share of the number of migrant children divided by young children as a share of the total number of children in the household. We regress this variable on school fees as the dependent variable in Equation (1) and found school fees to have no statistically significant impacts (not shown).

Table 5 Alternative measures of school fees and other robustness checks, China 2008

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	School fees	Tuition fees	School fees	School fees	School fees ('000 yuan)	School fees, urban
	Median	Median	p25	p75	Median	Median
Panel A						
School fees	-0.160** (0.068)	-0.129** (0.058)	-0.167*** (0.052)	-0.253** (0.118)	-0.107** (0.043)	-0.094** (0.047)
Observations	1,349	1,349	1,349	1,349	1,349	1,349
Mean of dependent variable	0.378	0.378	0.378	0.378	0.378	0.378
First-stage <i>F</i> statistics	15.146	15.807	8.150	11.610	13.256	7.229
	(7)	(8)	(9)	(10)	(11)	
	Tuition fees, urban	Control for income	Control for social protection spending	HP filter	2-Year lagged shock	
	Median	Median	Median	Median	Median	Median
Panel B						
School fees	-0.115** (0.051)	-0.137** (0.064)	-0.166** (0.077)	-0.157** (0.072)	-0.198** (0.085)	
Observations	1,349	1,349	1,349	1,349	1,349	
Mean of dependent variable	0.378	0.378	0.378	0.378	0.378	
First-stage <i>F</i> statistics	8.540	15.094	12.244	10.448	6.883	

Notes: Each column presents the results from separate IV regressions with different school fee measures and different independent variables, where the IV is the 1-year lag of shocks to public education spending. The dependent variable is a dummy variable that equals 1 if there is at least one child living with the household head in urban areas and 0 otherwise. The different measures of school fees under columns (1)–(7) are defined as follows: Column (1), log median school fees (including tuition fees, food and accommodation, remedial classes, and other fees) reported in the migrant sample; column (2), log median tuition fees reported in the migrant household sample; columns (3) and (4), log 25th percentile and 75th percentile school fees reported in the migrant household sample; column (5), median school fees (in '000 yuan) reported in the migrant household sample; column (6), log median school fees reported in the urban household sample; and column (7), log median tuition fees reported in the urban household sample. Columns (8)–(11) use the same measures of school fees as in column (1). In column (8), household income per capita is included as a control variable. In column (9), social protection spending per capita at the city level is included as a control variable. In column (10), the shocks generated by HP filter with smoothing parameter 6.25 is used as an instrument. In column (11), the sum of the public education spending shocks in 2005 and 2006 (linear filter) is used as an instrument. All regressions include the following controls: household heads' demographics, household heads' working variables, within province dummy variable, growth rate of student–teacher ratio, housing prices in 2007, industry FE, and original province FE. Standard errors in parentheses are clustered at the city level. ** $p < 0.05$, HP, Hodrick–Prescott; RUMiC, Rural–Urban Migration in China.

Sources: RUMiC 2008 and China City Statistical Yearbook 2002–2008.

4.2.2 Public versus private schools

Since public schools are generally considered to have higher quality than private schools in urban China (see, e.g., Goodburn, 2009), to what extent could our results be affected by the mix of school supply in different cities? Besides this quality difference, there can be a cost difference between these two types of school as well (e.g., public schools can charge migrant households the additional school selection fee (*Jie Du fee*)). As such, could migrant households consider

sending their children to the higher quality (and possibly more expensive) public schools or leave them behind, rather than choosing the (possibly less expensive) private schools? To investigate this issue, we implement several robustness checks as follows. First, we compare the various fees between public schools and private schools measured at the city level, which turn out not to be statistically different (except for the higher *Jie Du* fee charged by public schools, but the difference for this fee is only significantly different at the 10% level, not shown). Second, we rerun the estimates in Table 2 after dropping all the migrant children who attend a private school in the destination cities. Estimation results (Table 3.11 in the online Appendix 3) are very similar to those in Table 2. Finally, we rerun the estimates in Table 2 but focus only on the sample of migrant children who currently live in the cities and convert the dependent variable to a dummy variable that respectively equals 1 or 0 if the migrant child attends a public school or a private school. This regression can help us detect whether school fees can have an impact on the type of schools in the cities that migrant children attend. Estimation results, however, indicate that the estimated coefficients on school fees are not statistically significant (not shown).³⁴

4.2.3 Other robustness checks: additional control variables, IV probit model, alternative IV construction, panel data, robust standard errors, and cities with fewer observations

One concern is that the negative impacts of school fees could be caused by their correlation with migrant workers' income. We address this issue by controlling for income in the regressions (Table 5, column 8). Estimates are slightly smaller in magnitude but still qualitatively similar. To address the concern that our results can be biased due to unobservable characteristics that are both related to our IV and the macroeconomic conditions in the destination city, we further control for city-level gross domestic product per capita and its growth rate, but results are qualitatively similar (online Appendix 3, Table 3.12, columns 1 to 4). As another proxy for living costs in the city, we control for the minimum living expenses, but estimation results are qualitatively similar (online Appendix 3, Table 3.12, column 5).³⁵

As earlier discussed, we explicitly control for social protection spending in a robustness check and show estimation results in Table 5, column 9. The estimated coefficient on school fees does not lose its statistical significance when social protection spending is included, which supports the validity of the exclusion restriction. As an alternative, we also control for shocks to social protection spending instead of its level, but estimation results are still similar (online Appendix 3, Table 3.13).

An alternative modeling option besides the linear probability model is the probit model. The latter may be more appropriate if predictions from the former do not fit well in the range [0, 1] or the variance of the error terms heavily depends on the estimated model coefficients. Estimation results using the IV probit model, however, provide similar results (see Table 3.14 in the online Appendix 3).

³⁴ Yet, as a further check, we reestimated Table 2 and control for public schools as a share of the total number of schools in the cities. Estimation results (not shown) remained very similar.

³⁵ These expenses are, however, reported by the migrant households, so we do not rule out some degree of potential endogeneity issue.

We offer two additional ways to construct the IV. First, we apply the HP filter to generate shocks, and second, we use the sum of the shocks in the past 2 years. Estimation results are displayed in columns 10 and 11 of Table 5, which provide qualitatively similar results. Second, Figure 3.3 in the online Appendix 3 plots the predicted probabilities (based on Models 1 and 3 in Table 2) that the migrant worker brings his or her children and their upper bounds and lower bounds based on the Chernozhukov et al. (2013) method against the median school fees. The predicted probabilities reassuringly fall within the bounds.³⁶ Finally, we control for province-level CPI, which may proxy for unobserved macroeconomic shocks that can be related to shocks to public education spending. Estimation results (online Appendix 3, Table 3.15) provide qualitatively similar results.

There is a panel data component in the RUMiC survey between the two survey rounds of 2008 and 2009, but the attrition rate is quite high at 74%. Still, it can be useful to examine our estimation results using an individual fixed-effects model to test whether unobserved time-invariant individual characteristics may have influenced the migrant's decision to bring his or her children along. However estimates shown in Table 3.16 of the online Appendix 3 are qualitatively similar.

As suggested by Cameron and Miller (2015), we also experimented with obtaining the robust standard errors for few numbers of clusters using the user-written Stata command “*boottest*” (Roodman, 2017). The statistical significance levels (represented by the Wild Bootstrap Standard Errors (WRE) *p* values) remain rather similar (although they become somewhat weaker for mean school fees; see Table 3.17 of the online Appendix 3).

Finally, another potential issue with using the sample median (mean) or percentiles of fees is that the sample size in some cities can be rather small. For example, in the 2008 wave, there are few observations with school fee information for migrated children in Ningbo and Shenzhen. We thus exclude these two cities and reestimate our results; estimation results shown in Table 3.18 of the online Appendix 3 are, however, similar.

4.3 Heterogeneity analysis

4.3.1 Vulnerable migrant households

We check whether our estimation results still hold for different groups of migrant households by estimating our main specification (column 3 of Table 3) on each subsample and offer results in Table 3.19 of the online Appendix 3. Indeed, estimation results suggest that higher school fees deter poor migrants (i.e., those who fall in the lower half of the household income distribution) from bringing their children with them (row 1), as do migrants without insurance (or social benefits) (row 2), with a short-term work contract (row 4), with only one child (row 7) and, to some extent, the depressed (row 6).³⁷ The impacts of school fees are also statistically

³⁶ Since the predicted probabilities from Model 2 are rather similar to those from Model 3, we do not plot them to make the graph easier to read.

³⁷ For each migrant worker, RUMiC records the enrollment status of four major social insurances/benefits: unemployment insurance, pension insurance, work injury insurance, and housing fund (*San Xian Yi Jin*), which are mandated by the Social Insurance Law. We define a migrant worker as insured if he/she has access to at least one of these insurances/benefits. We record whether the household head is depressed by comparing the subjective well-being questions against the questions of Center for Epidemiological Studies Depression Scale. We recode the answers to the questions about depression such that higher scores imply a more intense state of depression. We define a person as depressed if the summation of his or her scores is greater than 22.

Table 6 Median school fees and child migration during the economic crisis, China 2009

Variable	(1)	(2)	(3)
Median school fee (Ln), (OLS)	-0.226*** (0.043)	-0.148*** (0.046)	-0.121*** (0.044)
Median school fee (Ln), (IV)	-0.449*** (0.154)	-0.440 (0.311)	-0.408 (0.359)
Observations	1,005	1,005	1,005
Mean of dependent variable	0.305	0.305	0.305
HH's employment variables and industry (FE)	No	Yes	Yes
Growth rate of student-teacher ratio	No	Yes	Yes
Housing prices in 2008	No	No	Yes
First-stage <i>F</i> statistics	22.310	3.371	1.605

Notes: Each column presents the results from separate IV regressions with different independent variables, where the IV is the 1-year lag of shocks to public education spending. The dependent variable is a dummy variable that equals 1 if there is at least one child living with the household head and 0 otherwise. Regressions use the median school fees reported in the migrant household sample as a regressor. Similar to Table 2, household head's demographics and original province FE are controlled in all the columns, and additional sets of control variables are included in columns 2 and 3. *R*-squared values are not reported, instead RMSE, the sample standard deviation of the differences between the predicted values and observed values, is reported under each column. Standard errors in parentheses are clustered at the city level. $\text{Prob} > \chi^2$ is the *p*-value of the chi-square test of overall significance. *F* statistics of the first-stage regressions are also reported. ****p* < 0.01, FE, fixed effects; HH, household; IV, instrumental variable; OLS, ordinary least squares; RMSE, root mean square error; RUMiC, Rural-Urban Migration in China.

Sources: RUMiC 2009 and China City Statistical Yearbook 2002–2009.

significant for households who migrated to non-coastal cities: Zhengzhou, Luoyang, Hefei, Bengbu, Chongqing, Wuhan, and Chengdu (row 3). These results hold for migrant households with both spouses in the city (row 8) or with only one spouse (not shown)³⁸ and for employees (not shown) and the self-employed (row 9).

4.3.2 School fees and child migration during the economic crisis

As earlier discussed, our theoretical intuition suggests that child migration would increase in response to the reduced school fees in 2009 but would decrease during the economic crisis in the same year. Which effect would dominate child migration? Estimation results using the 2009 wave of the RUMiC survey show that the non-IV estimates (Table 6, row 1) are negative, and are between 60% and twice larger in absolute magnitude than those for 2008 (bottom of Table 2). Since the upward biased non-IV estimates provide lower bound estimates of the true impacts of school fees, this offers evidence that the negative effects of the economic crisis dominate the positive effects coming from a reduction in school fees. Furthermore, even though our IV is severely weakened for the crisis year (as discussed in Section 3.3) and thus could only offer statistically significant estimates in one specification (column 1), the IV estimates have

³⁸ A recent study estimates that 35% of LBC live with a single parent (Kong and Meng, 2010).

Table 7 Child migration and well-being, China 2008

Variable	(1)	(2)	(3)
	Underweight	Overweight	Child health
Migrated with parent(s)	0.023 (0.252)	-0.214** (0.105)	0.263 (0.292)
Child's age	0.001 (0.007)	-0.017*** (0.005)	0.002 (0.007)
Child's gender	0.065*** (0.023)	-0.020* (0.012)	0.038 (0.032)
Head's age	-0.007 (0.006)	0.003 (0.002)	-0.004 (0.005)
Head is female	0.032 (0.044)	-0.001 (0.025)	-0.062 (0.063)
Head's height	-0.003 (0.003)	0.001 (0.001)	0.006 (0.004)
Head completed primary school	-0.070** (0.028)	-0.016 (0.026)	0.108*** (0.041)
Head completed middle school	0.020 (0.033)	-0.000 (0.022)	-0.006 (0.039)
Constant	1.293*** (0.436)	0.220 (0.209)	3.298*** (0.780)
Observations	1,556	1,556	1,673
Mean of dependent variable	0.504	0.084	4.339
Original province FE	Yes	Yes	Yes
RMSE	0.495	0.287	0.682
Prob > χ^2	0.000	0.000	0.000
First-stage <i>F</i> statistics	20.901	20.901	23.231

Notes: Each column presents the results from separate IV regressions with different school fee measures and different independent variables, where the IV is the 1-year lag of shocks to public education spending. The dependent variables in columns (1)–(3) are defined as follows: column (1), dummy variable indicating underweight (BMI<18.5); column (2), dummy variable indicating overweight (BMI>25); column (3), subjective health score on a 1–5 scale, with a larger score indicating more satisfaction; for migrant children, this question is answered by themselves; for left-behind children, this question is answered by their migrant parents. *R*-squared values are not reported. Instead, the RMSE, the sample standard deviation of the differences between the predicted values and observed values, is reported under each column. Standard errors in parentheses are clustered at the city level. Prob > χ^2 is the *p*-value of the chi-square test of overall significance. *F* statistics of the first stage regressions are also reported. ****p* < 0.01, ***p* < 0.05, and **p* < 0.1. FE, fixed effects; RMSE, root mean square error; BMI, body mass index; RUMiC, Rural–Urban Migration in China.

Sources: RUMiC 2008 and China City Statistical Yearbook 2002–2008.

the expected negative sign and are two to three times larger than those of the non-IV estimates. These results concur with those for Table 2.^{39,40}

5 Further analysis of health outcome

Our theoretical intuition suggests that children brought along by migrant households may have better non-schooling outcomes, such as improved health. This result is strongly supported

³⁹ We ran the same regressions with mean school fees, which provide qualitatively similar results (see Table 3.20 of the online Appendix 3).

⁴⁰ Since we do not have data on migrants' province of original residence for 2009, we do not control for these dummy variables. An alternative modeling option is to pool the 2008 and 2009 rounds of the RUMiC for analysis. While this option allows us to employ a richer econometric model by controlling for the year and city fixed effects, it does not offer more insights into the crisis year as discussed earlier. Still, estimation results using the pooled data (Table 3.21 of the online Appendix 3) are qualitatively similar.

by most, if not all, of the recent studies on China as discussed earlier. We reexamined this result with the RUMiC data and investigated whether moving with parents impacts their body mass index (BMI) and the underweight/overweight status.⁴¹ We regressed these child health outcomes on a dummy variable indicating whether the child is living in the city with the migrant household, controlling for children's and the household heads' characteristics. The endogenous variable here is the child migration dummy variable, and the IV is the public education spending shocks (the first-stage regression in this case is the reduced form regression). Unlike the previous regressions that were run at the household level, we ran these regressions at the individual level for all the school-age children in the sample. Estimation results (Table 7) indicate that moving with parents is associated with a lower probability of being overweight (column 2) and has no statistically significant correlation with being underweight (columns 1 and 3).⁴²

6 Conclusion

We add to the literature by investigating a major constraint to parental migration—school fees—that affects their children's welfare. We provide new empirical evidences that point to the harmful effects of increased school fees (across major cities in China) on migrant households' decisions over whether to bring with them their children, the number of children to bring, and the gender of the children they bring. Moving with parents could benefit migrant children with better health outcomes and lower risks of being overweight. These effects are robust to different measures of school fees and to different techniques used to construct the instrumental variable. Further heterogeneity analysis shows that vulnerable migrant households are more impacted by school fee changes, and the negative effects of higher school fees may possibly be larger during an economic crisis.

Our study is relevant to the Chinese context or any other country that is undergoing a large-scale rural–urban migration process. Remarkably, China's growing rural–urban dualism creates social tensions and increasingly becomes a constraint for further labor-market integration, urbanization, and economic development. Even though the country has abolished school fees starting in late 2008, in practice, migrant households are still found to be obliged to pay various school-related fees. Thus, our results can lend quantitative supportive evidence to the removal of school fees by the government and similar policies aimed at improving migrants' access to public service irrespective of their place of residence (see, e.g., Hu et al., 2008). Our findings also suggest that the central government may consider better targeted budget transfers to local governments that would specifically address migrant children's education. If inclusive urbanization is to be accomplished, local governments could focus on achieving social welfare objectives (in particular, better access to education for migrants) besides purely economic objectives.

41 The BMI, a measure of tissue mass (muscle, fat, and bone) in an individual, is computed as the ratio of weight (in kilograms) to squared height (in meters). Using World Health Organization's guidelines, we consider that children with a BMI less than 18.5 and equal or greater than 25 are, respectively, underweight and overweight.

42 We also investigate whether higher school fees prevent migrant workers from bringing their children with them to the city and thus encourage them to send education remittances back home instead. Estimation results indeed suggest that 10% increase in school fees results in an increase of between 241 and 304 yuan in the annual remittances (Table 3.22 in the online Appendix 3). However, greater remittances may not necessarily result in better outcomes for LBCs; a recent study by Démurger and Wang (2016) points to a strong negative impact of remittances on education expenditures in remittances-receiving households as remittances lead to increased consumption, possibly at the expense of investments.

Declarations

Availability of data and material

The RUMiC survey data is available from the International Data Service Center (IDSC) of IZA. The other variables used in the regressions and a Stata program are available from the authors upon request.

Competing interests

None.

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Authors' contributions

H.-A. Dang, Y. Huang and H. Selod jointly contributed to the analysis and writing of the paper. The authors read and approved the final manuscript.

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Appendix 1: Description of Chernozhukov et al. (2013) bounds and application procedures

Focusing on the instrumented impacts of school fees through the 1-year lag of shocks to public education spending only, we can rewrite Equation (1) in a more general form as a conditional expectation:

$$E\{Y_{ik,t}(Fee)|Shock_{ik,t-1} = \xi\} \quad (A1)$$

where the outcome of interest (or indicator function) $Y_{ik,t}$ is defined at time t as before and ξ as the different values of shocks to public education spending at time $t-1$. Only two assumptions are required for the Chernozhukov et al. bounds. One is the *monotone instrumental variable* (MIV) assumption, where the conditional expectation in Equation (A1) is assumed to weakly increase in ξ , for all values of school fees. The other assumption is the *monotone treatment response* (MTR) assumption, where the indicator function $Y_{ik,t}$ is assumed to increase in the level of school fees.

There is an inverse relationship between the migrant worker's decision over his child migration and shocks to public education spending or school fees; thus; we multiply both the school fees and shocks variables with -1 to make this relationship positive. This does not affect our estimation results since estimates can be plotted against the original values of school fees. The MIV assumption is then satisfied, given a strong correlation of 0.69 between $Y_{ik,t}$ and the shocks variable; the MTR assumption is satisfied as discussed earlier (see Figure 2). Besides these two assumptions, no additional assumption is made about the IV.

To obtain meaningful analysis, the support of Y needs to be bounded. We can consider the probability that the migrant worker brings his or her children along to the city, which is defined as follows:

$$P^* = P\{Y_{ik,t}(Fee) \geq 1 | Shock_{ik,t-1} = \xi\} \quad (A2)$$

Under the MIV and MTR assumptions, the Chernozhukov et al.'s upper bound and lower bound are, respectively,

$$P^* \leq \inf_{u \geq \xi} E\{1(Y_{ik,t} \geq 1) * 1(Fee \leq \Psi_{ik,t}) + 1(Fee \geq \Psi_{ik,t}) | Shock_{ik,t-1} = u\} \quad (A3)$$

and

$$P^* \geq \sup_{u \leq \xi} E\{1(Y_{ik,t} \geq 1) * 1(Fee \geq \Psi_{ik,t}) | Shock_{ik,t-1} = u\} \quad (A4)$$

where $1(\cdot)$ is the indicator function. We set ξ at its median value 0.36, and the support values for the lower bound and the upper bound thus range from -1.04 (its minimum value) to 0.36 and 0.36 to 3.82 (its maximum value). By varying the bounds in Equations (A3) and (A4) over the whole range of values of school fees ($\Psi_{ik,t}$), we can then trace out these bounds. We estimate these bounds using the Stata command "*clr2bound*" provided in Chernozhukov et al. (2015).

Appendix 2: Data Sources

A.1 Rural–Urban Migration in China (RUMiC) 2008

RUMiC is a longitudinal survey that is specifically designed to study migration in China. The survey consists of three parts: the Urban Household Survey (5,000 households), the Rural Household Survey (8,000 households), and the Migrant Household Survey (5,000 households). It was initiated by a group of researchers at the Australian National University, the University of Queensland, and Beijing Normal University and was supported by Institute for the Study of Labor (IZA), which provides the Scientific Use Files. Financial support for RUMiC was obtained from the Australian Research Council, the Australian Agency for International Development, the Ford Foundation, IZA, and the Chinese Foundation of Social Sciences.

Our analysis is mainly based on the migrant household module of 2008. The migrant household sample covers 15 cities of the nine-largest provinces sending and receiving migrants. These are Bengbu, Chengdu, Chongqing, Dongguan, Guangzhou, Hefei, Hangzhou, Luoyang, Nanjing, Ningbo, Shanghai, Shenzhen, Wuhan, Wuxi, and Zhengzhou. The sampling frame of migrant households was generated on the basis of the census conducted by the RUMiC project team. Data are collected on household members' characteristics, education, employment, health, general well-being, income, expenditure and assets, as well as left-behind household members.

Websites: <https://www.rse.anu.edu.au/research/centres-projects/rural-urban-migration-in-china-and-indonesia/> and <http://idsc.iza.org/?page=27&id=58>

A.2 China City Statistical Yearbook 2002–2008

The China City Statistical Yearbook is an annual statistical publication. The China City Statistical Yearbook 2002–2008 compiles various statistical data for the period 2001–2007 of 657 organizational system cities (including cities at and above prefecture-level and county-level cities). We use the education spending at the metropolitan area level from 2001 to 2007.

Website: <http://www.stats.gov.cn/tjsj/ndsj/>

Compiling institution: National Bureau of Statistics of China

Publisher: China Statistics Press

A.3 China Urban Life and Price Yearbook 2008

The China Urban Life and Price Yearbook is a compilation of information from China Urban Household Income and Expenditure Compendium and Price Yearbook of China. It contains urban household income and expenditure records, the main indicators of general urban development, the main indicators of urban life quality, and urban price levels. We use the 2007 housing price records at the city (metropolitan area) level.

Website: <http://tongji.cnki.net/overseas/engnavi/YearBook.aspx?id=N2009030074&floor=1>

Compiling institution: National Bureau of Statistics of China

Publisher: China Statistics Press