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The effect of parental migration on children left behind: meta-analytical evidence on education and child labour

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Abstract: This study presents meta-analytical evidence of the effects of parental migration on children left behind. To systematically analyse the existing empirical findings, we identified 33 papers with 577 estimates on education and child labour that were circulated between 2000 and March 12th, 2024. We complemented these with another 13 papers on educational aspirations that were systematically reviewed. Employing automated tools to increase the objectivity of our approach (*litsearchr, ASReview)*, we find that on average children left behind show worse educational outcomes and are more likely to work than non-migrant children with no clear effect on educational aspirations. Yet, there is considerable heterogeneity. Children left behind in China show improved educational outcomes and less child labour. The consolidated evidence calls policymakers of countries with high emigration and/or internal labour migration to be aware of the possible challenges faced by left-behind children and to provide programs and safety nets for them.

Keywords: Meta-regression analysis; systematic review; children left behind; education; child labour; low- and middle-income countries

1. Introduction

International migration rose from 153 million to 281 million individuals between 1990 and 2020 (UN, 2020). These figures do not include the largest movement of people, internal migrants, estimated to be 763 million people in 2013 (Bell & Charles-Edwards, 2013). Even though there are no recent estimates of internal migration, these migratory flows keep increasing due to urbanisation (McAuliffe & Oucho, 2024). Despite (humanitarian) crises being a migration trigger, most migrants move to improve their family's financial situation by being economically active in another area (Stark & Bloom, 1985; UN, 2022; Zentgraf & Chinchilla, 2012). Accordingly, there has been a significant rise in remittances over the past years (UN, 2022).

Yet, a downside of economic migration is that families cannot necessarily migrate together and have to split up. Often this implies that children are left behind in vulnerable conditions (Antia, Rodoreda, & Winkler, 2022; UN, 2022). In countries as diverse as Georgia, Ghana, Moldova, China, the Philippines, Ecuador, and South Africa, about one-third of the children are estimated to be left behind by a migrating parent (Fellmeth et al., 2018). They stay in their original living environment whilst one or both parents migrate, often for work. Connecting them to essential services, such as education, might be difficult without parents because of financial instability immediately after parental departure, increased household obligations, and less parental care and support (Bakker, 2009; UNICEF, 2021). Moreover, these left-behind children are more at risk of human rights violations, such as abuse and neglect (Bakker, 2009; UNICEF, 2021), implying new challenges for child protection (Fu et al., 2023). Therefore, it is crucial for policymakers to have systematic evidence of the impact of parental migration on their left-behind children.

With the meta-analysis and systematic review at hand, we structurally analyse and synthesise the results of the existing literature to contribute to a more robust evidence base about the net effect of parental migration (Grames et al., 2019; Xu, 2017). While meta-regression analyses are not uncommon in economics and development (Floridi, Demena, & Wagner, 2020), there is a knowledge gap in systematic evidence regarding the effects of parental migration on educational and child labour outcomes of left-behind children in low-and middle-income countries (LMICs). Existing meta-analyses focus either on health outcomes or exclusively zoom in on China (Chen et al., 2020; Fellmeth et al., 2018; Wen et al., 2021). Moreover, to the best of our knowledge, no meta-analysis includes the effect of parental migration on child labour, although narrative reviews and primary studies are available (Asis & Ruiz-Marave, 2013; Yang, 2004). Consequently, we aim to answer the following research question: *"How does parental migration affect educational and child labour outcomes of the children left behind in LMICs?"*

We meta-analyse 577 estimates from 33 studies on education and child labour outcomes and systematically review another 13 papers on educational aspirations circulated between 2000 and March 12th, 2024. We searched the following platforms: Scopus, Web of Science, and Google Scholar. We find that on average the experienced family disruption outweighs the financial benefits derived from parental migration. Children left behind show worse educational outcomes and are more likely to work than non-migrant children. However, there is heterogeneity in effects. For China, financial gains from migration spur educational outcomes and child labour decreases. The effect of parental migration on educational aspirations remains unclear in the existing literature.

This study contributes to the current literature in the following six ways. First, we broaden the focus on both educational and child labour outcomes for all LMICs, making our meta-analysis the most comprehensive study related to the topic to date. Partly, this is because the evidence base keeps growing due to ever-increasing migratory dynamics (UN, 2022), resulting in improved consistency and generalisability of the aggregate results (Dekkers, Carey, & Langhorne, 2022). Second, aggregate, across-study outcomes are important since individual studies measuring parental migration on children's educational outcomes at a single point in time potentially suffer from bias related to the timing of the data collection (Wassink & Viera, 2021). Third, our meta-analysis benefits from employing tools such as *litsearchr* and *ASReview*. This increases the objectivity of our structural approach (Grames et al., 2019; Van De Schoot et al., 2021). Fourth, the meta-analysis also contributes to the literature by examining the heterogeneity of effects, as these very likely depend on the context in which parental migration occurs (Fellmeth et al., 2018). Fifth, focusing on the effect of migration in the sending countries contributes to the geographical decentring of migration research away from the current focus on Western receiving countries. Sixth, the meta-analysis at hand further adds to the migration debate as it is one of a few studies analysing internal and international migration jointly.

The remainder of this article is structured as follows: Section 2 presents a brief literature review. Section 3 introduces the data and methodology. The results, including robustness and heterogeneity analyses, are presented in section 4 and section 5 concludes.

2. Literature review

Family-related migration topics are increasingly represented in migration journals, resulting in a growing evidence base on the consequences of parental migration on left-behind children (Pisarevskaya et al., 2020). Many studies have been conducted in China, where the phenomenon of left-behind children is widespread as a result of the household registration (Hukou) system. This system does not grant the same rights to rural-urban migrants as to urban-born citizens. Excluding the former from access to school and health care (Jingzhong & Lu, 2011; Lu, 2012). Studies have also been conducted in other countries where migration is relatively common, such as Mexico, India, and the Philippines (Pajaron, Latinazo, & Trinidad, 2020; Song & Glick, 2022; Vikram, 2021). Despite the growing evidence base, inconclusive impacts of parental migration on the educational and labour outcomes of children left behind were identified. The three main channels discussed in the literature are the income, substitution, and aspiration channel, which differ in their predicted effects of parental migration.

On the one hand, migrant parents send back remittances, which can be used to educate left-behind children (Bryan, Chowdhury, & Mobarak, 2014). This income effect – sometimes referred to as the economic pathway – increases schooling and decreases the probability of engaging in child labour (Gassmann et al., 2018; Roy, Singh, & Roy, 2015; Zambrana Cruz & Rees, 2020). In similar vein, the aspiration channel suggests increased educational aspiration due to parental migration. Migrating parents shift the educational aspirations for their children upwards by exposing them to new conditions and environments (Beine, Docquier, & Rapoport, 2001; Böhme, 2015). Children know about the sacrifices that their parents made and consequently aspire more (Chen et al., 2013). Since children left behind are more likely to migrate themselves (Chen, 2023), the prospect of future migration increases the expected return to education and, thus, educational investments.

On the other hand, the lack of parental care and attention might outweigh the improved financial means and negatively affect educational outcomes (Lu, 2014; Raut & Tanaka, 2018; Wang et al., 2021). Fu et al. (2023) point out that remittances are mainly used to pay off debt and to fulfil basic needs, such as buying food. Moreover, the emotional distress or lack of a parental caregiver can lead to lower school performance. Related insights stem from the literature on the consequences of divorce on children's educational outcomes (Bernardi & Radl, 2014; Bussemakers, Kraaykamp, & Tolsma, 2022; Havermans, Botterman, & Matthijs, 2014). The changes in parental time and practices, the increase in parental stress, and the child's emotional distress due to parental absence might apply similarly to parental migration. Resource dilution theory further suggests that if only one instead of two parents is available, parental social resources and support decrease due to less time and energy (Blake, 1981; Steelman & Powell, 1989). This leads to less cognitive stimulation of the child. However, children from divorced and migrant parents also differ from each other. Divorced parents often live closer to their children than migrant parents, while migrant parents can be more involved than recently divorced parents (Nobles, 2011; Yu, 2013). This can result in different (financial) contributions to the household and, accordingly, different educational outcomes (Nobles, 2011; Yu, 2013).

Related to distress and lack of attention is the substitution or family disruption channel that suggests that children might have to replace their missing parent in the household, which makes them particularly vulnerable to child labour (Chang, Dong, & MacPhail, 2011; Kamei, 2018; Xu, 2017). The aspirations of children can be affected as well. Since migration is experienced as an alternative option, children left behind are more likely to migrate themselves, which might paradoxically lower educational aspirations (Chen et al., 2013; Wassink & Viera, 2021). This is referred to as the 'culture of migration hypothesis', which predicts that as many people in the community migrate irrespective of their educational achievements, children might not see the expected return to education (Dreby & Stutz, 2012). Taken together, the substitution channel could mitigate the positive effects of the income channel.

Empirical assessments of these theoretical insights resulted in a wide array of evidence. For the case of Romania, Botezat and Pfeiffer (2020) show that children experiencing parental migration show a 2.4 higher grade point average on a 1-to-10-point scale compared to children living with both parents. Similarly, Vikram (2021) finds that Indian children left behind by their father have a 0.5 higher reading test score on a five-point scale compared to children living with both parents. The effect is particularly strong for boys. Regarding child labour outcomes, Pajaron, Latinazo and Trinidad (2020) identified for the case of the Philippines that children left behind were less likely to work compared to children living with both parents. All these studies support the income channel.

In turn, there is also evidence for the opposite effect, suggesting that the substitution channel dominates the relationship between parental migration and children's skills. Wang et al. (2021) show for the case of China that children experiencing maternal migration have two years less of schooling compared to children who do not experience any parental migration. Chang, Dong and MacPhail (2011) look at the child labour outcomes for Chinese children who are left behind. They find that children left behind are more likely to participate in domestic and agricultural work. Daughters left behind by one parent increase their daily domestic work by an hour and sons by 20 minutes.

Next to educational outcomes, other studies focus on the aspirational effects (Dreby & Stutz, 2012; Kandel & Kao, 2001; Nobles, 2011; Wen et al., 2015). Nobles (2011) shows that Mexican children experiencing parental migration have lower aspirations to go to college as compared to children who do not experience migration. This supports the findings from earlier work of Kandel and Kao (2001), who similarly identified that Mexican children experiencing paternal or family migration have lower aspirations to go to university. In turn, Dreby and Stutz (2012) present evidence that Mexican children who experience maternal migration aim for a higher educational level. Similarly, Wen et al. (2015) demonstrate that paternal and parental migration increases children's educational aspirations in China.

To understand the heterogeneity in the observed effects, depending on the specific contexts in which parental migration takes place, we draw on attachment theory (Wang et al., 2023) and the transnational family literature (Haagsman & Mazzucato, 2014; Parreñas, 2005; Zentgraf & Chinchilla, 2012). Both theories observe differences in effects depending on the age of the child. According to attachment theory, parental migration at a younger age – during a critical period of attachment – leads to more adverse effects for the child (Wang et al., 2023). If attachment formation to a key caregiver is interrupted, separation, social anxiety and other mental health issues can appear, which can negatively influence educational attainments (Wang et al., 2024). Critical attachment periods happen between 0 and 7 years of age (Liu, Li, & Ge, 2009). Others suggest that key attachment is completed by age 6 (Ling, Fu, & Zhang, 2015) or even age 3 (Altenhofen et al., 2013). Parental absence after these critical periods is less adverse since children can develop some resilience associated with successful attachment (Bender & Ingram, 2018). This way, children can better cope with parental migration and put it in a social perspective, especially when they grow up in an environment where out-migration is prominent (Wang et al., 2023; Zentgraf & Chinchilla, 2012).

The role of a child's age at separation is less clear in the transnational family literature, that has been extensively reviewed by Haagsman and Mazzucato (2014). On the one hand, separation at a younger age might be traumatic because the child cannot fully comprehend the situation (Fan et al., 2010; Schmalzbauer, 2004). On the other hand, parental migration could be traumatic at older ages when shared memories have been made, and the child misses the parent more actively. Other mediating factors discussed by Haagsman and Mazzucato (2014) are the gender of the migrant parent, the contact between parent and child, remittances sent, the quality of the substitute caregiver, and the length of separation. The effects of parental migration are worse for maternal migration and if the relationship between the migrant parent and the caregiver is conflicted due to divorce or differences in caregiving approaches (Haagsman & Mazzucato, 2014; Jingzhong & Lu, 2011). Moreover, frequent contact and remittances seem to influence the parent-child relationship positively (Haagsman & Mazzucato, 2014). The role of separation length is unclear in the literature. Longer separation can emotionally distance the parent and child more (Carling, Menjívar, & Schmalzbauer, 2012; Fresnoza-Flot, 2009). However, there is also evidence that children value their parents more because of what they sacrificed for them (Schmalzbauer, 2008).

To identify commonalities in this literature, our meta-analysis systematically consolidates the existing studies to assess the overall impact of parental migration on children's education and labour activities, accounting for variations in effects, conditions, and methodologies. We also account for heterogeneities due to the timing of the primary study, the country under study, sample characteristics, gender, and publication traits.

3. Data & methodology

3.1 Data

For this systematic review and meta-analysis, three databases and two search rounds were used to examine the published literature: Scopus and Web of Science during the first search round and Google Scholar during the second search round. Articles in Scopus and Web of Science circulated between the year 2000 and February 24th, 2023, when the first search round was performed, were searched for. The year 2000 was chosen as a starting point because the ILO added the Worst Forms of Child Labour Convention in 1999 (ILO, n.d.). Since 2000, this definition has remained unaltered, and we expect that the convention has spurt research into the situation of children. A second search round was performed using Google Scholar, which was done on February 24th, 2024. The second search round was used to investigate the grey literature and whether an additional search round affects the results of our study, akin to the approach in previous research (Fellmeth et al., 2018; Floridi, Demena, & Wagner, 2020). The tailored search strings for each database can be found in Appendix 1. Keywords around three concepts were combined: 1) parental migration, 2) children left behind, and 3) child educational and labour outcomes. The search strings for Web of Science and Scopus were optimised using the *litsearchr* package in R, an automated approach using text mining and keyword co-occurrence networks to make the search strategy more reproducible, standardised, and less susceptible to biases (Grames et al., 2019).

We explicitly focused on quantitative English-language studies on parental migration, children left behind, and educational and child labour outcomes in LMICs based on the PICOC protocol by Petticrew and Roberts (2008). The *population* concerns children aged 5-17 who experienced parental absence of at least one migrant parent. The age range is based on the minimum working age as defined by the ILO, the Convention on the Rights of the Child, and reports of international organisations like UNICEF (ILO & UNICEF, 2021; Unicef, 1989). Parental absence due to parental internal or international migration of at least one parent for at least 6 months is taken as the *intervention* for educational outcomes since this is considered problematic by the international community (Antia et al., 2020; Fellmeth et al., 2018). Papers for which the mean duration of parental migration was above 6 months are also included. For child labour outcomes, the *intervention* is parental internal or international migration without the 6-month rule since a child often fills up an immediate gap in household chores when a parent leaves (Chen, 2013). Following previous research, the population of children with at least one migrant parent is *compared* to children from non-migrant households (Antia et al., 2020; Fellmeth et al., 2018). The study focuses on educational and child labour *outcomes*, ranging from educational attainment to school dropout and from child labour as incidence to hours and days worked, in the *context* of LMICs. Appendix 2 shows the complete list of outcomes considered in this study. In line with previous studies by Fellmeth et al. (2018) and Floridi, Demena and Wagner (2020), studies that were not written in English, not accessible without paying a fee, qualitative, using ANOVA only, and/or did not have sufficient data to perform the needed calculations were excluded.

After each search round, the review proceeded in two stages. In stage one, articles were marked as relevant or irrelevant based on the information in their titles and abstracts. In stage two, the articles marked as relevant were read entirely and inspected more intensively by looking at the data and methods. Two researchers (ALE & EB) identified relevant and irrelevant articles in this study. The researchers reviewed the titles, abstracts, and papers independently and discussed potential differences resulting in reconciliation. The first search round resulted in 421 papers in Web of Science and 372 in Scopus, leading to a total of 793 papers to be screened in the selection process. Duplicates were removed, leaving 637 articles to be reviewed in stage one. These papers were reviewed using *ASReview*, a machine learning technique that applies active learning to make screening more effective, transparent, and less susceptible to biases (Van De Schoot et al., 2021). The program ran based on 7 key papers identified by the authors, 5 relevant and 2 irrelevant articles, that were used as prior knowledge to train the algorithm and to create the order in which papers are shown to the users (Van De Schoot et al., 2021). In principle, one relevant and one irrelevant paper are sufficient for the algorithm to run, but we included several articles related to the PICOC strategy to improve efficiency and effectiveness (Van De Schoot et al., 2021). Afterwards, the researchers actively (re)trained the algorithm by selecting relevant studies based on the title and abstract provided (Van De Schoot et al., 2021).

This process continued until the previously determined stopping rule was reached (see Appendix 3 for more detailed information about the stopping rule), for which the main criterion is the adequacy of including all relevant papers and excluding all irrelevant papers (Van De Schoot et al., 2021). The golden standard for this process is human reviewers, who tend to have an average error rate of around 10% (Wang et al., 2020). Following previous research using *ASReview*, a combination of two rules is used: (1) stop when the estimated number of relevant papers in the dataset is reached, based on the formula by Van Haastrecht et al. (2021), (2) stop when 50 papers in a row are labelled irrelevant (Ros, Bjarnason, & Runeson, 2017; van Dee, Schnack, & Cahn, 2023; Van Haastrecht et al., 2021). The latter prevents overestimating the number of relevant papers and screening inefficiently and is widely applied (Loheide-Niesmann, Riem, & Cima, 2022; Ros, Bjarnason, & Runeson, 2017; van Dee, Schnack, & Cahn, 2023). After reviewing 474 abstracts and titles, 50 papers in a row were deemed irrelevant, and screening was stopped (see Appendix 4). At this point, 74.41% of the articles were screened. According to Van De Schoot et al. (2021, p. 130) in their assessment of *ASReview*, “95% of the eligible studies will be found after screening between only 8% to 33%

of the studies", which means we reached the golden standard. The remaining 194 relevant articles were thoroughly investigated during stage two. During this stage, 45 additional duplicates were removed, which had not been removed before because of formatting or spelling differences. Ultimately, we extracted data from 21 eligible papers in this first search round for the analysis.

The Google Scholar search round resulted in 396 additional articles to be screened. Since the data needed for *ASReview* could not be exported, the articles from Google Scholar were reviewed manually. To determine when to stop screening during the first stage, the knee method was applied as implemented in the KneeArrower package in Rstudio since it is reliable, performs well regarding recall, and is efficient (Cormack & Grossman, 2016; Tseng, 2020). The knee point of inflexion is calculated by the slope ratio before and after a critical inflexion point on the gain curve, which is based on the articles screened and the number of relevant articles out of those articles (König et al., 2023). To determine when to stop, both the derivative cutoff and the maximum curvature cutoff points have been used (Tseng, 2020). See Appendix 5 for detailed results from the knee method for both child labour and educational outcomes. This resulted in 46 additional non-duplicate articles to be reviewed in depth by looking at the full texts in stage two. In the end, 12 additional papers were included in the analysis.

Two final complementary searches were performed using hand searching and backward snowballing. Hand searching was used to ensure that we have not missed out on the grey literature, such as reports by international organisations, which are harder to find through the databases used in this paper (Dekkers, Carey, & Langhorne, 2022). The databases of the World Bank, UNICEF, NBER, ILO, IOM, IMF, the Asian Development Bank, UNESCO, OECD, and the African Development Bank were checked. No additional quantitative reports/articles using regression analysis were found. After having the complete set of initial articles, backward snowballing was performed to include related research found in the initial set of relevant articles (Dekkers, Carey, & Langhorne, 2022; Floridi, Demena, & Wagner, 2020). The backward snowballing resulted in 3 additional relevant articles, for which data was extracted.

The various search rounds and stages have led to the extraction of 577 estimates from 33 papers. Appendix 6 shows the selection process using the PRISMA diagram. None of the estimates includes odds ratios or relative risk ratios, as only 6 of the 80 odds ratio estimates reported the needed standard errors. Most studies were excluded because they were qualitative, investigated children left behind for less than 6 months or due to a different control group. 13 additional papers on educational aspirations were systematically reviewed to explore the aspiration channel in addition to the quantitative meta-analysis. These studies came from the systematic search in Scopus, Web of Science, and Google Scholar but were excluded from the meta-analysis because they did not fulfil the inclusion criteria outlined in the PICOC strategy.

3.2 The meta-dataset

After the final selection of articles, the data was extracted. In particular, data on the outcomes (see Appendix 2), the intervention, the years for which data was obtained, the geographical region, the income level of the country based on the World Bank Analytical Classifications (World Bank, 2023), the number of observations, whether the data comes from primary or secondary sources, the study design, and publication characteristics. The heterogeneity in the data was handled as follows. First, the outcome variables were divided into positive education variables (such as years of schooling), negative education variables (such as dropout), and child labour outcome variables. The child labour outcomes are also divided into 4 groups for subsample analysis: (1) unpaid domestic work, (2) unpaid farmwork, (3) paid work, (4) family business work. All four categories were classified as child labour in the original studies. The intervention variables were divided into binary and continuous left-behind variables.

Variables on the study design included whether the analysis measures a marginal effect, whether the coefficient comes from a linear, log-lin, or lin-log regression, whether the regression was weighted, whether an interaction term was included, and the number of explanatory variables. Regarding the estimation technique used, we used the following categories: (1) ordinary least squares, (2) instrumental variable analysis/two-stage least squares, (3) fixed effects, (4) structural equation modelling, and (5) other techniques, such as random effects, etcetera. A variable was created to show whether or not a quasi-experimental method was used. Regarding fixed effects, we collected data for year-fixed effects, household and individual fixed effects, as well as regional and district fixed effects. Next, gender, age, education level, the number of children in the household, wealth, and remittances were coded as variables the original study controlled for in the estimation. Finally, specific subsamples of the original papers were coded: (1) boy or girl samples, (2) mother or father migrant samples, (3) international or internal migration samples, (4) one or two migrant parent samples, (5) various age samples, (6) samples indicating whether the effect is long-term, short-term, or not specified, and (7) whether the sample comes from a rural/undeveloped or from an urban/developed area.

Next to the study design, publication characteristics were retrieved from the studies. In particular, the year and month of publication, whether the publication was reviewed or not, Google Scholar citations, the 5-year impact factor as specified in the Journal Citation Reports of Clarivate, and the Recursive Discounted Impact Factors for Journals from IDEAS RePEc. The publication age was calculated based on the year and month of the publication. Lastly, the search round was also coded. Search round 1 indicates the search done in Web of Science and Scopus, and search round 2 indicates the search done in Google Scholar and the backward snowballing. Table 1 shows the definition and descriptive statistics of the variables used in the meta-analysis.

We include estimates from 17 countries. Most estimates included in this meta-analysis focus on positive educational outcomes, namely 54%. The largest group of studies looks at years of education as the dependent variable, followed by hours spent on school-related work, school enrolment, and test scores. 38% of the estimates address child labour outcomes. The variable hours worked was used as the dependent variable in most of these studies, followed by child labour dummies (working/not working).

Only 8% of the estimates focus on negative educational outcomes. These studies look equally often into disruption and dropout. Most estimates concern the binary left-behind identifier (86%). Left-behind children are mainly studied in Asia, representing 90% of the estimates, while only 1% focuses on Africa, 2% on Europe, and 7% on North America. The majority of the Asian studies analyse Chinese data as internal rural-urban migrants have to leave their children behind due to the complex residential system (Dollar, 2014; Li, 2023; Zhang, 2023). Additional studies come from India and Vietnam. Studies about Africa are equally distributed between Burkina Faso, Kenya, and Senegal. All studies on Europe come from Romania. Mexico and El Salvador are the countries from Northern America. No studies have been identified for South America.

The income levels (low, lower-middle, and upper-middle) of the investigated countries are quite evenly spread out. Many studies do not specify which type of migration they look at; we know explicitly that 9% of the estimates consider international migration and 29% internal migration. The dominance of Chinese studies on rural-urban migration is likely to drive this. Most estimates derive from fixed effects estimations, but ordinary least squares and the instrumental variable approach are also common. About half of the estimates resulted from search round one and the other half from search round two. About 69% of the estimates come from peer-reviewed studies. The data used in the original studies mainly stem from the 1990s and the 2000s. The first publication year was 2006, and the most recent publication year was 2024. Interest in the topic seems to be emerging recently, with the average year of publication being 2017. The coefficients reported per study vary between 1 and 104, with each study reporting 17 estimates on average.

3.3 Methodology

Following previous meta-analyses by Demena, Floridi and Wagner (2022) and Floridi, Demena and Wagner (2020), with various economic outcome and predictor indicators, a standardisation approach is used to make the effect sizes comparable. As suggested by the Reporting Guidelines for Meta-Regression Analyses in Economics of Stanley et al. (2013), the partial correlation coefficient is used as follows (Stanley and Doucouliagos (2012, p. 25):

Table 1: Descriptive statistics

Definition	Mean	St. Dev.	Min	Max	N
Outcome characteristics					
Effect size (regression coefficient)	1.20	11.46	-5.74	230.34	577
Standard error of the effect size	1.13	7.44	-4.42	167.12	577
T-statistic	0.35	2.19	-10.81	7.41	577
Winsorized PCC	0.01	0.05	-0.10	0.09	577
Standard error of the winsorized PCC	0.03	0.01	0.01	0.05	577
# of explanatory variables	12.95	6.43	0	35	577
Positive education variables	0.54	0.50	0	1	577
Negative education variables	0.08	0.27	0	1	577
Child labour variables	0.38	0.49	0	1	577
Intervention dummies					
Left behind	0.86	0.35	0	1	577
Left behind measured as a continuous variable	0.14	0.35	0	1	577
Data characteristics of the studies					
Data collection started in the 1980s	0.12	0.33	0	1	577
Data collection started in the 1990s	0.31	0.46	0	1	577
Data collection started in the 2000s	0.36	0.48	0	1	577
Data collection started in the 2010s	0.21	0.41	0	1	577
# of observations	92,632.87	627,681.30	112	5,696,236	577
Low-income countries	0.35	0.48	0	1	577
Low-middle income countries	0.34	0.47	0	1	577
Upper-middle income countries	0.31	0.46	0	1	577
Data from Asia	0.90	0.30	0	1	577
Data from Africa	0.01	0.10	0	1	577
Data from Europe	0.02	0.15	0	1	577
Data from North America	0.07	0.25	0	1	577
Estimation characteristics					
Instrumental variable approach	0.19	0.39	0	1	577
Fixed effects regression	0.44	0.50	0	1	577
Other estimation techniques	0.35	0.48	0	1	577
Quasi-experimental method	0.02	0.15	0	1	577
Interaction	0.11	0.32	0	1	577
Controlled for in specification					
Education of household head	0.15	0.36	0	1	577
Number of children in the household	0.70	0.46	0	1	577
Income or assets of the household	0.52	0.50	0	1	577
Subsamples in studies					
Girl sample	0.18	0.38	0	1	577
Boy sample	0.16	0.37	0	1	577
Mother migrant sample	0.14	0.35	0	1	577
Father migrant sample	0.51	0.50	0	1	577
Internal migration sample	0.29	0.45	0	1	577
International migration sample	0.09	0.28	0	1	577
Age sample (yes/no)	0.91	0.29	0	1	577
Immediate effect	0.19	0.40	0	1	577
Long-term effect	0.14	0.35	0	1	577
Publication characteristics					
Year of publication	2017	4.54	2006	2024	577
Reviewed publication	0.69	0.46	0	1	577
Google Scholar citations	37.93	69.86	0	452	577
Search round 2	0.46	0.50	0	1	577

Note: [a] Discrepancies in the means summing to one are due to rounding.

$$PCC = \frac{t}{\sqrt{t^2+df}} \quad (1)$$

with t denoting the t-statistic of the multiple regression coefficient and df the degrees of freedom of the t-statistic. The PCC shows the relationship between the intervention and the educational or child labour outcome, holding other variables constant (Stanley & Doucouliagos, 2012).

In addition, we checked for outliers in our dataset using two different approaches. With the minimum covariance determinant, we determined a mean based on 75% of the sample. Based on this mean, outliers were identified using the Mahalanobis distance for each data point. The threshold determining data points as outliers is based on the chi-squared distribution. This led to an exclusion of 51 observations, which is 9.5% of the sample. As a second approach, we winsorized the data, cutting off 5% on each side. This way, 10% of the sample was winsorized (replaced with less extreme values). The latter is thus the more conservative approach, which we will continue to use in the ensuing analyses.

To summarise the meta-analysis data, we follow the Reporting Guidelines for Meta-Regression Analysis in Economics (Stanley & Doucouliagos, 2012; Stanley et al., 2013). First, the effect sizes are summarised by simple and weighted average effect sizes. The weighted average of this effect size is calculated using the inverse of the variance as outlined by van Aert and Goos (2023). Since studies and estimates can suffer from publication bias, we also look at funnel plots and perform a regression test for funnel plot asymmetry to estimate whether publication bias is present. Next, the Funnel-Asymmetry Test (FAT) and Precision-Effect Testing (PET) are used to determine the size of the publication bias and the genuine effect size of parental migration on economic and child labour outcomes (Dekkers, Carey, & Langhorne, 2022; Stanley & Doucouliagos, 2012). The FAT and PET tests are represented as follows (Stanley & Doucouliagos, 2012, pp. 60-61):

$$PCC_i = \beta_0 + \beta_1 SE_i + \varepsilon_i, \quad (2)$$

where PCC_i is an individual PCC estimate and SE_i is the associated standard error. β_1 represents the FAT and β_0 the PET (Stanley & Doucouliagos, 2012). Since this equation can suffer from heteroskedasticity and within-study dependence, we use Weighted Least Squares, dividing equation (2) by its standard error SE_i (Floridi, Demena, & Wagner, 2020; Stanley & Doucouliagos, 2012):

$$t_i = \beta_0(\frac{1}{SE_i}) + \beta_1 + v_i, \quad (3)$$

where t_i is the t-statistic of each PCC estimate, which is obtained by PCC_i/SE_i, β_0 is the PET, β_1 the FAT, and v_i is ε_i/SE_i (Floridi, Demena, & Wagner, 2020; Stanley & Doucouliagos, 2012).

As a baseline model, we use OLS with study-level clustered standard errors. Additionally, we check for study-level effects using a Breusch Pagan Lagrange Multiplier Test (Stanley & Doucouliagos, 2012). The results can be found in Appendix 7, which shows no study-level effects for negative educational outcomes.

Yet, there are study-level effects for the positive educational outcomes and child labour. We, therefore, also show a mixed-effects-multilevel (MEM) model. Since the Hausman test to decide between the fixed- or random-effects model (Stanley & Doucouliagos, 2012; Wooldridge, 2010) cannot be performed for our data as the underlying assumption of se(β_{1FE}) $> se(\beta_{1RE})$ is violated (Wooldridge, 2010), we opted for the fixed effect (FE) model, which is also a better predictor under publication bias (Stanley & Doucouliagos, 2012). Note that the random effects assumption of no correlation between unobserved characteristics and the predictor variables is also often violated in meta-analyses (Stanley & Doucouliagos, 2012).

To account for country-specific time-varying factors such as emigration rates, we also perform the OLS and MEM models with country- and decade-fixed effects. Finally, following previous research by Floridi, Demena and Wagner (2020), a Jack-knife experiment is performed to investigate whether particular individual studies influence the results. This is done by excluding one study at a time and re-estimating the genuine effect using the remaining studies.

Last, heterogeneity analyses are performed by adding moderator variables, such as publication, methodological, and empirical characteristics of the studies, to disentangle the effect of these variables from the genuine effect and assess their impact on the estimates (Dekkers, Carey, & Langhorne, 2022; Floridi, Demena, & Wagner, 2020; Stanley & Doucouliagos, 2012). We employ the following model:

$$(4)\ t_i = \beta_0 \left(\frac{1}{SE_i}\right) + \beta_1 + \frac{a_k X_k}{SE_i} + v_i,$$

where t_i is the t-statistic of each PCC estimate, β_0 is the PET, β_1 is the FAT, a_k is the vector of estimated parameters, X_k represents the category of a particular moderator and v_i is ε_i/SE_i. In line with previous research, the general-to-specific approach has been used to construct the final model for each outcome category (positive educational outcomes, negative educational outcomes, and child labour outcomes) (Floridi, Demena, & Wagner, 2020; Stanley et al., 2013). Only moderators without multicollinearity were included, and the most insignificant moderators were removed (based on p-values). This leads to a unique model for every outcome category. For positive educational outcomes, 15 of the 33 potential moderators were used in addition to the inverse of the standard error. The joint F-test for these moderator variables is F(15, 236) = 25.7 (p-value = 0.000), supporting the joint significance of the moderators used. The model using all potential 33 moderators has an F(33, 218) = 0.681 (p-value = 0.828), showing no joint effect. For negative educational outcomes, only 3 of the 10 additional moderators were used. The joint F-test for these moderators is F(3,42) = 13.935 (p-value = 0.000), suggesting that they are not only individually but also jointly significantly different from zero. The model using all potential moderators had the following value: F(10,35) = 1.633 (p-value = 0.1590). For child labour outcomes, we used 6 additional moderators out of 16 potential moderators. The 6 moderators used have an F(6,127) statistic of 8.278 (p-value = 0.000). The model using all potential moderators does not have explanatory power: F(16,117) = 0.846 (p-value = 0.586).

The I^2 statistic shows that significant between-study heterogeneity remains (see Appendix 8) (Fellmeth et al., 2018; Harrer et al., 2021; Higgins & Thompson, 2002). The between-study variation is quantified as the percentage of variability in the effect sizes that is not caused by sampling error and is considered as substantial if more than 75%. To determine why heterogeneity in the results is observed (Harrer et al., 2021), subgroup analyses are performed for each search round and for the publication status (peer-reviewed or not). Next, China vs. other countries and country-income categories are examined. Moreover, subgroup analyses are performed on immediate and long-term effects, for different kinds of child labour, and intensive vs. extensive margins.

4. Results

4.1 Average effects

The average effect sizes suggest that parental migration has no practical effect on educational and child labour outcomes. Table 2 first shows summary statistics of the overall impact of parental migration on positive educational outcomes. The weighted average effect is 0.0067. This is statistically significant at the 1% level. It does, however, not imply any practical relevance. A meta-regression coefficient of less than 0.07 is considered small according to Doucouliagos (2011). Moreover, the unweighted coefficient is negative albeit insignificant. The results for negative educational outcomes show a similar picture. For child labour outcomes, the found effects are equally small in absolute terms but both are statistically significant at conventional levels. In sum, these overall results do not point towards strong impacts from parental migration on the education and labour outcomes of the left-behind children.

Table 2: Estimates of the overall impact on every outcome category

	Effect size	S.E.	95% Confidence Interval	
Positive educational outcomes				
Simple average effect	-0.0013	0.0028	-0.0069	0.0043
Weighted average effect	0.0067***	0.0020	0.0027	0.0106
Negative educational outcomes				
Simple average effect	0.0159**	0.0065	0.0029	0.0289
Weighted average effect	0.0005	0.0063	-0.0122	0.0133
Child labour outcomes				
Simple average effect	0.0123***	0.0027	0.0069	0.0177
Weighted average effect	0.0056**	0.0027	0.0003	0.0109

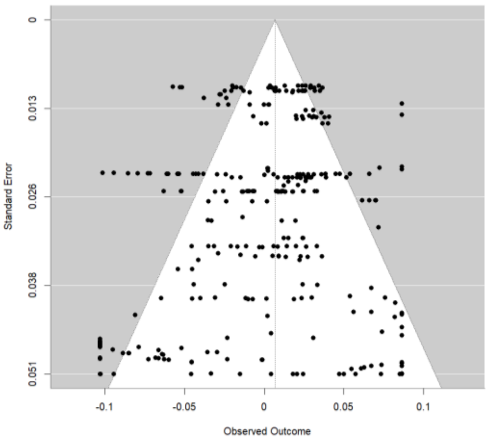
*Note: *** p<0.001, ** p<0.05*

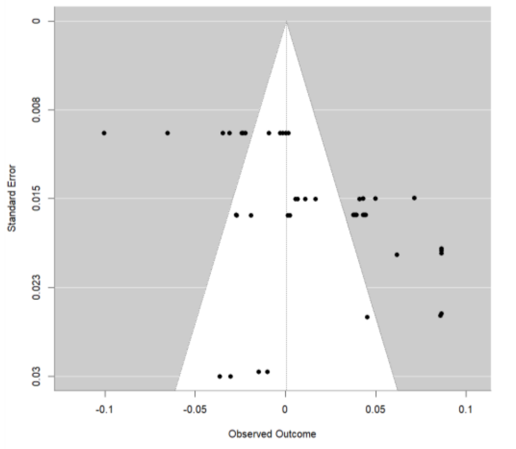
4.2 Genuine effects and publication bias

Next, we study whether publication bias, implying that not all results are published or distributed to a similar extent, influences the results (Stanley & Doucouliagos, 2012). First, we use funnel plots and regression tests. In Figure 1, the vertical dotted line shows the average weighted effect size. From eyeballing the figures, asymmetry in all three plots can be observed, suggesting the presence of publication bias (Floridi, Demena, & Wagner, 2020; Harrer et al., 2021). For the positive educational outcomes, studies with larger standard errors and negative estimates seem scarce compared to those with small standard errors. This is confirmed by the regression test for funnel plot asymmetry, which can be found in Appendix 9. The test is significant at the 1% level and has a coefficient of 0.015, meaning that the expected observed effect of a study with a standard error of 0 would be 0.015. Regarding the negative educational outcomes, studies with more precision/larger studies seem to report larger negative effects. Yet, the regression test for funnel plot asymmetry cannot be interpreted as only 4 studies look at negative educational outcomes, which results in too little power for the test (Harrer et al., 2021). The funnel plot for child labour is also asymmetrical. There seem to be fewer smaller studies/studies with less precision. There also seems to be some clustering of studies with smaller standard errors that report more positive outcomes. The regression test for funnel plot asymmetry shows that asymmetry is significant. The limit coefficient shows that the expected genuine effect of a study with a standard error of 0 would be -0.014. Overall, based on this initial visual analysis, there is some indication of publication bias, but the extent is rather low.

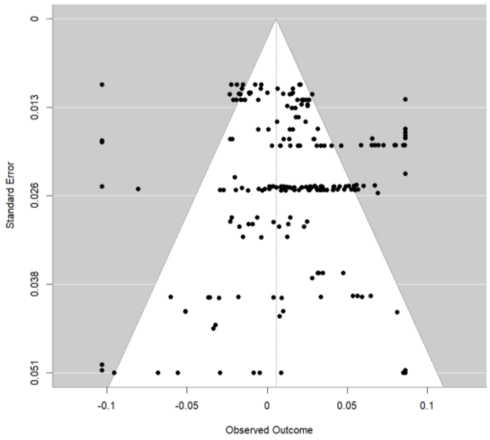
Figure 1: Funnel plots for educational and child labour outcomes

Positive educational outcomes Negative educational outcomes





Child labour outcomes



Yet, the interpretation of the graphical funnel plot is subjective. Therefore, we performed the FAT and PET analyses in addition (Harrer et al., 2021; Stanley & Doucouliagos, 2012). FAT estimates the publication bias and PET the related genuine effect. Results with clustered standard errors are presented in Table 3. For positive educational outcomes, our largest sample of observations, the Breusch-Pagan Lagrange Multiplier test showed that the MEM is most suitable for this data. Therefore, our analysis of the results for this outcome will focus on this model, taking the other models into account as robustness checks. Across the three models, there is no evidence of publication bias in studies looking at positive educational outcomes. The publication bias coefficient of our preferred MEM is -0.017 and is statistically insignificant. The MEM estimates that children left behind show improved educational outcomes compared to children living with both parents, with a coefficient of 1.056 that is statistically significant at the 10% level. This genuine effect is, however, not consistent across the three models. The other two report a zero impact. The evidence for the effects of parental migration on negative educational outcomes is more consistent across the three models. For this outcome variable, the most appropriate model is the fixed effect model; it suggests worsened educational outcomes for children left behind with a statistically significant coefficient of 7.540. Concerning publication bias for papers studying negative educational outcomes, we obtain mixed results. The FE estimate suggests that reported coefficients underestimate the genuine effect, reflected in a statistically significant negative publication bias coefficient of -0.096. Yet, the MEM suggests no publication bias. Lastly, the child labour studies display consistent PET and FAT coefficients across all three models. Evidence shows that children left behind are more likely to work yet the effect is insignificant. The MEM estimates a non-significant coefficient of 3.430. Moreover, the FAT coefficient suggests a slight downward publication bias of -0.053; however, it is equally statistically insignificant. Results without clustered standard errors can be found in Appendix 10 and are more likely to identify significant effects. We attribute the

Table 3: Genuine effect and publication bias for every outcome category

	Dependent variable: t value		
	OLS (Clustered SE) (1)	Fixed Effects (Clustered SE) (2)	Multilevel Random Effects (Clustered SE) (3)
Positive educational outcomes			
Genuine effect (PET)	-0.512 (0.642)	0.121 (0.678)	1.056* (0.592)
Bias (FAT)	0.015 (0.013)	0.006 (0.015)	-0.017 (0.014)
Observations		310	
Studies		18	
Negative educational outcomes			
Genuine effect (PET)	5.463** (2.505)	7.540** (1.394)	0.307 (3.319)
Bias (FAT)	-0.071** (0.031)	-0.096** (0.015)	0.002 (0.067)
Observations		46	
Studies		4	
Child labour outcomes			
Genuine effect (PET)	1.297 (1.004)	3.394 (2.217)	3.430 (3.108)
Bias (FAT)	-0.014 (0.018)	-0.044 (0.035)	-0.053 (0.055)
Observations		221	
Studies		15	

Note: **p<0.1;* ***p<0.05;* ****p<0.01*

lack of statistical significance with the clustered standard errors to the increased rigour and consider these more conservative findings as more reliable.

In order to account for time-varying country-specific factors, such as emigration rates, we also show the estimation results with country and decade-fixed effects for positive educational and child labour outcomes in Appendix 11. These fixed effects models could not be estimated for negative educational outcomes because there were not enough observations for each category. Once these fixed effects are controlled for, the genuine effect of parental migration on positive educational outcomes becomes negative in the OLS model but loses its significance in the multilevel model. For child labour outcomes, the effect remains positive and insignificant but increases in magnitude. Thus, overall, we cannot identify strong evidence for the negative repercussions of parental migration on children left behind in terms of educational and labour outcomes.

Before proceeding to the multivariate analysis, we examine the impact of excluding each study individually from the analysis. We perform a Jack-knife experiment for our main regression specifications, the MEM with clustered standard errors for positive educational outcomes and child labour and FE with clustered standard errors for negative educational outcomes. Table 4 displays these findings. For positive educational outcomes, the results from these tests are mostly consistent with our main findings in Table 3, suggesting a positive effect

Table 4: Jack-knife experiment

Study	Genuine effect	Bias	Dropped	Total observations
Positive educational outcomes - MEM				
1	1.1224*	-0.0155	4	306
2	1.0189*	-0.0169	4	306
3	1.2201**	-0.0199	70	240
4	1.2230**	-0.0172	40	270
5	1.1480*	-0.0175	29	281
6	0.2821	0.0014	16	294
7	1.0457*	-0.0168	6	304
8	1.0065*	-0.0172	3	307
9	0.9829	-0.0166	7	303
10	1.2055**	-0.0174	6	304
11	1.0938	-0.0203	48	262
12	1.0823*	-0.0167	6	304
13	1.1239*	-0.0169	4	306
14	1.1087*	-0.0170	1	309
15	0.8608	-0.0199*	6	304
16	1.0564	-0.0164	52	258
17	1.1034*	-0.0172	6	304
18	1.0372*	-0.0173	2	308
Negative educational outcomes - FE				
1	7.1960***	-0.0931***	7	39
2	0.7845	0.0187	12	34
3	8.4861***	-0.1064***	4	42
4	6.115*	-0.084	21	25
Child labour outcomes - MEM				
1	3.5358	-0.0570	1	220
2	4.9212	-0.0843	28	193
3	3.5837	-0.0530	4	217
4	3.7198	-0.0572	4	216
5	3.3208	-0.0532	3	218
6	5.6462	-0.0913	52	169
7	3.6983	-0.0572	3	218
8	4.1569	-0.0716	12	209
9	-0.0478	0.0101	30	191
10	3.7544	-0.0560	2	219
11	3.2330	-0.0489	40	181
12	3.6653	-0.0542	16	205
13	3.4719	-0.0558	9	212
14	3.5873	-0.0549	1	220
15	3.5997	-0.0592	16	205

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

on educational outcomes with a very small insignificant negative publication bias. Thus, it does not seem that a single study drives the identified overall effects. For negative educational outcomes, the results are also consistent with Table 3 with a positive genuine effect and a small negative publication bias. Yet, the variation in the findings is larger. It seems that one study drives the strong positive and statistically significant effects. For child labour outcomes, the Jack-knife experiment confirms that there is no statistically significant effect of parental migration. Yet again, one study seems to drive the large positive coefficient estimate.

4.3 Accounting for heterogeneity across studies: multivariate analysis

The inconclusiveness of the findings presented so far might be explained by the remaining unexplained heterogeneity in effects (Floridi, Demena and Wagner, 2020). To account for this, we employ a multivariate analysis. For positive educational outcomes, all three multivariate model specifications confirm that parental migration significantly affects children's educational outcomes negatively once controlled for the moderators (Appendix 12). Regarding publication bias, some downward bias is found for positive educational outcomes; it is statistically significant at conventional levels only for the FE and the MEM.

Studies that measure negative educational outcomes confirm a worsening of educational outcomes due to parental migration (Appendix 13). All employed models show that negative educational outcomes, such as school dropout, are more often observed for children left behind than for children not experiencing parental migration. Again, we identify a significant negative publication bias. Yet, these results should be interpreted with a grain of salt since they are derived from a small sample with only 46 observations.

Lastly, all multivariate specifications for child labour outcomes show that children left behind are more likely to work (Appendix 14). The child labour papers also show a significant downward publication bias across all three multivariate models. For all three outcomes studied we conclude from the multivariate analysis, that the findings support the substitution channel.

Heterogeneity, as seen in the I^2 statistics in Appendix 8, can explain the differences across primary studies. The moderator analysis shows that the effect of being left behind on positive educational outcomes depends on various methodological choices and the sample used. The results are consistent across models (see Appendix 12). Importantly, studies employing quasi-experimental methods tend to identify more negative effects suggesting that observational studies might be suffering from attenuation bias. In addition, the multivariate analysis points to the importance of individual level control variables. The education level of the household head seems key here and studies controlling for it tend to report less negative effects. Similarly, studies controlling for age tend to report less negative effects. The effect on both the girl and boy samples is more negative than on the sample that does not specify gender. If the father is the migrant parent of the child left behind, the effect is less negative. Finally, studies that are cited more seem to report lower t-values.

Looking at negative educational outcomes, gender disaggregated analyses point towards more nuanced findings with smaller impacts (Appendix 13). If the study specifies whether girls or boys left behind are considered, the magnitude of the effect of parental migration is smaller.

Regarding child labour outcomes, the empirical approach used in the original study is consistently associated with the effect of parental migration on left-behind children (Appendix 14). The instrumental variable approach leads to larger effects, whereas quasi-experimental studies lead to effects smaller in magnitude. In line with the findings for negative educational outcomes, if the original study specifies whether it looks at boys or girls, the estimated effect is smaller in magnitude, although across models these effects do not consistently show up as significant difference. Similar to positive educational outcomes, the estimated effect also depends on the quality of the study as reflected by the Google Scholar citations. Studies that are cited more report bigger impacts on child labour.

4.4 Sub-sample analysis

Appendices 15-20 show the results for different sub-sample analyses; taking into account the moderators used in section 4.3, we further explore the heterogeneity in results. Yet, only the results for positive educational outcomes, referred to as educational activity for this section, and child labour outcomes are shown because there are too few observations in the sample of negative educational outcomes. Related to this, for the FE and MEM regressions, it was impossible to compute robust clustered standard errors in the sub-samples due to a lack of observations.

We first discuss the findings for short versus long-term effects which are only available for educational outcomes (Appendix 15). The sub-sample analysis shows that the results found in the previous section are robust over time.

We also clearly see that the relationship between parental migration and the educational activity of children left behind are context dependent. Appendix 16 shows the results for China versus other countries since most of the research is done for children left behind in China. Although we still identify publication bias for both samples, the results show that the impact of parental migration in China seems to be different from that of other countries. In particular, studies about China find a significant and positive effect for educational activity and a significantly negative effect for child labour outcomes (for the OLS and the FE estimations). In the other countries, we find the opposite. Namely, significantly negative effects on educational activity and significantly positive child labour outcomes. This suggests that the income channel is the driving force in China, while the substitution channel is more dominant in the other countries. This could be because Chinese society is more aware of children left behind, which also makes policy-makers more cognisant of their situation.

Another sub-sample analysis was performed for low-, lower-middle-, and upper-middle-income countries to see whether a country's income level plays a role in the impact of parental migration on left-behind children (Appendix 17). Indeed, this seems to be the case. For educational activity, we identify negative effects for every income level but the upper-middle income countries. These effects are statistically significantly different from zero for the OLS and FE models for the upper-middle income countries and for the FE models for the remaining income categories. For child labour, we find positive and often significant effects for low- and lower-middle-income countries, while a significantly negative effect has been found for upper-middle-income countries in the OLS and FE model. Yet, all estimates of the child labour sample for upper-middle-income countries come from China, implying that the results represent China's unique situation. We further observe some publication bias in all of the income-level sub-samples. Overall, for upper-middle income countries the income effect seems to dominate.

Results disaggregated by the different types of child labour can be found in Appendix 18. Children left behind seem to conduct more unpaid domestic work, as we can observe a significantly positive effect in all model specifications. We also find positive effects for unpaid farmwork, but this is only significant for the FE estimation. The coefficients for unspecified work are significantly positive as well. At the same time, the OLS and FE specifications for paid work show that children left behind perform significantly less paid work. The coefficient for the MEM is similarly negative but not significant. It is not surprising that left-behind children seem to take over household chores that were before performed by the missing parent. The intensive versus extensive margin findings seem related. Children left behind work more hours than children who were not (Appendix 19). Based on the analysis for the intensive margin, children seem to work more hours in general, as all coefficients are significantly positive. For the extensive margin, we find both significantly positive and negative effects. It can thus not be discerned whether children start or quit working, i.e. they might stop doing paid work and start unpaid domestic work. Across most of the type of work and intensity specifications, we identify publication bias; it is weakest for unpaid farm work.

Finally, we checked whether the peer-review process had an impact on the findings. Interestingly, Appendix 20 shows that publication bias seems to be bigger for non-peer-reviewed articles. In addition, the child labour coefficients are bigger (and significantly positive), and the impact on educational activity seems to be positive instead of negative compared to peer-reviewed articles. Consequently, it seems that researchers of the non-peer-reviewed articles are more inclined to present results that align with their expectations, yet these might not survive the scrutiny of the review process.

4.5 Systematic review of the aspiration channel

In addition to the income and substitution channel, this study examines the aspiration channel. Since few aspirational studies were deemed relevant for inclusion in the meta-analysis according to our PICOC definitions and some were qualitative, we opted for systematically reviewing the studies on aspirations; 13 of the 15 relevant studies were included because 2 were inaccessible. All studies make conclusions about the effect of parental migration on the educational aspirations of children left behind; however, they measure aspirations in different ways. In one-third of the studies, aspirations are measured by a variable indicating the highest level of education that the child would wish to achieve (Dreby & Stutz, 2012; Hu, 2019; Wen et al., 2015; Xu et al., 2018). The study by Chen and Hesketh (2021) takes the same approach but compares it to educational expectations (measured in the same way but asked as a reflection on what the children think they will achieve) to measure the aspiration-expectation gap. Yu (2013) and Mao, Zang and Zhang (2020) take the same approach but turn it into a dichotomous variable reflecting whether or not the child aspired to study until college or higher. Another 2 papers measure aspirations as a continuous variable in years of schooling that the children would wish to obtain (Chen et al., 2013; Lu et al., 2023). Case studies and interviews with either teachers or children were used 5 times; 3 studies asked teachers specifically (Ayala, 2017; Hu, 2019; Ullah, Naz, & Wadood, 2024) and 2 studies observed and asked the children themselves (Hu, 2019; Jingzhong & Lu, 2011). The research by Wassink and Viera (2021) takes an entirely different approach, comparing the educational attainment of children left behind in high-migration communities to communities with low migration rates to test the 'culture of migration hypothesis'.

The 13 papers examine 3 countries and 2 regions: Asia and North America. 8 papers examine the case of China, 1 focuses on Pakistan, and another 4 studies examine the Mexican situation. Thus, the studies are largely conducted in upper-middle-income countries. Almost all these studies have been published in peer-reviewed journals except for 2, which are Master's theses. The first publication year was 2011, and the most recent year was 2024. Compared to the educational and child labour papers, this is 5 years later, suggesting that the focus in the literature was first on the income- and substitution channel. About half of the studies use primary data, and the other half use secondary data. 8 papers use quantitative methods, 3 papers use qualitative methods, and 2 papers use mixed methods. Propensity score matching was used 3 times as was (ordered) logistic regression. Other popular methods were interviews, ANOVA, and OLS regressions. Zooming in on the results, there is no clear effect of parental migration on the educational aspirations of children left behind. A summary can be found in Table 5; 3 studies point toward a negative relationship, 1 toward a positive effect, and the rest finds mixed results. The results differ between the main analysis and sub-group analyses focusing on a specific parent migrating. There is no clear relation-

Table 5: Frequency table of the aspirational papers*

	Insignificant impact	Significant negative impact	Significant positive impact	Qualitative: positive impact	Qualitative: negative impact
China					
Main analysis	5	2		1	
Sub-sample: mom migrant	2				
Sub-sample: father migrant	1		1		
Sub-sample: both migrants	1		2		
Sub-sample: one migrant parent			1[1]		
Pakistan					
Sub-sample: father migrant					1
Mexico					
Main analysis	1	1[2]			1
Sub-sample: mom migrant			1		
Sub-sample: father migrant	2	1			
Sub-sample: both migrants		1			

Note: *Only categories for which data is available are shown. [1]The outcome variable measured the aspiration-expectation gap. [2]The treatment variable refers to living in a low- or high-migration-prevalence community.

ship between which parent migrates and the direction of the effect. Similarly, the method does not seem to influence the results. Overall, a clear relationship between parental migration and educational aspirations has yet to be established.

5. Conclusion and discussion

As migration is creating challenges for child protection, this study performs a meta-analysis to synthesise current evidence on children left behind with regard to educational and child labour outcomes (Botezat & Pfeiffer, 2020; Chang, Dong, & MacPhail, 2011; Fu et al., 2023; Marchetta & Sim, 2021). Studies on various educational and child labour outcomes were gathered according to the PICOC strategy and analysed according to the Reporting Guidelines for Meta-Regression Analysis in Economics (Petticrew & Roberts, 2008; Stanley et al., 2013). We systematically retrieved 577 estimates from 33 papers and another 13 papers for a systematic review on educational aspirations. All studies were circulated between 2000 and March 12th, 2024, and are available in Scopus, Web of Science, and Google Scholar. Of the 33 papers, 15 focus on child labour outcomes, 5 on negative educational outcomes, and most of them (18) on positive educational outcomes. 90% of the estimates are for Asian countries. The first publication year was 2006, and the most recent publication year was 2024, with an increasing trend in studies over time indicating that being left behind due to parental migration is a contemporary problem and reinforcing the need for synthesising the existing findings.

The simple average and weighted effects did not suggest any practically significant effect of parental migration on children's educational and labour outcomes. Similarly, publication bias seems to be limited and inconsistent across models, with inconsistency being attributable to heterogeneity. Once we control for study characteristics in the multivariate analyses, publication bias seems to be present in all models. In turn, publication characteristics do not consistently influence the effect of parental migration on children left behind. Only the Google Scholar citations, corrected by age of the publication, has explanatory power for the educational activity and child labour. The original study samples and the empirical approach taken seem to be the most important sources of heterogeneity. Similarly, heterogeneity is considerably influenced by gender disaggregation and the use of quasi-experimental methods. Most importantly, we see clear evidence in the multivariate analyses that parental migration of at least 6 months adversely affects educational outcomes and increases child labour. Taken together, the results suggest that the substitution channel dominates the income channel. No concrete conclusions can be made about the aspiration channel based on a systematic review of 13 relevant papers since the results are inconsistent. This relationship needs more attention in future research.

The sub-sample analysis for short-term versus long-term effects shows that the results found for educational activity are robust over time. The overall negative effects of parental migration on children's human capital are also confirmed when looking at long-run labour market outcomes of left-behind children (Liu et al., 2020). Individuals who were left behind as children earn lower wages and are in less stable adulthood employment conditions. Moreover, the sub-sample analyses clearly show that the relationship between parental migration and the educational and labour outcomes of children left behind is largely context-dependent. Chinese studies and studies on upper-middle income countries find a significant and positive effect for educational activity and a significantly negative effect for labour outcomes. For the other countries, we find the opposite. In addition, we find evidence that children left behind engage in less paid work, possibly because their family's income situation improved. However, at the same time, we observe more child labour in unpaid work, suggesting that they replace their missing parent's contribution to household chores. Overall, children left behind work more hours. Lastly, the results for peer-reviewed versus non-peer-reviewed articles suggest that publication bias is bigger for non-peer-reviewed studies.

These results have important implications for policymaking. Various studies have demonstrated that institutional barriers tend to prevent migrant parents from bringing their children along (Li, 2023; Zhang, 2023). This situation can have long-term (educational) consequences on the affected children and in turn on the economic growth of a country as well (Hanushek & Woessmann, 2010; Shen, Hu, & Hannum, 2021; UNICEF, 2021). Moreover, since the substitution channel dominates the income channel in most countries, it is important to uphold the rights of children when their parents migrate. To counteract the negative effects of parental migration, governments could promote substitutes for parental attention, e.g. in the form of an increased number of social workers or specialised assistance to the substitute caregiver in the extended family.

Since parental migration does not necessarily have to have a negative effect on educational outcomes or a positive effect on the child labour outcomes of children left behind, as shown by the sub-sample analysis of China, further research on the Chinese approach seems warranted. Moreover, there are still considerable gaps in the literature. First, data collected on narrower age ranges, the amount of contact between the child left behind and the migrating parent, the distance between the place of origin and destination, and the characteristics of the substitute caregiver would have further enriched the analysis at hand. These factors are shown to play a role in the relationship between migrant parent and child but are hardly collected (Haagsman & Mazzucato, 2014). Second, only 5 studies examine negative educational outcomes. More research should investigate both these negative educational outcomes (such as lagging behind in school) and aspirational educational outcomes to fully understand the family substitution, income, and aspiration channels. Third, only 1% of the studies in this meta-analysis focuses on the African continent, and no studies have been found for South America. Yet, the latest World Migration report of the IOM (2024) shows that migration in these two continents has increased tremendously since the 1990s. Accordingly, it is important to look at the consequences of parental migration on educational and child labour outcomes for children left behind in Africa and South America as well. Fourth, future studies should clearly specify whether they look at internal or international migration, whether one or two parents are migrating, and how long they migrate for. Fifth, the adverse effects of parental migration on children left behind might have further worsened during the COVID-19 years. Remittances dropped worldwide during this period, but migrant families were often excluded from social protection programmes since they slipped through the social security net as the “new poor” (Zambrana Cruz & Rees, 2020). Thus, further research on the effect of parental migration during the global pandemic is warranted to understand the role of large shocks. Sixth, using non-migrant families as a control group does not allow for perfect identification of the effect of parental migration on educational outcomes. Caarls et al. (2018) show that transnational families differ from non-transnational families in observable characteristics such as age of childbirth and the number of relationships from which children result. Arguably, migrant families also differ from non-migrant families in terms of non-observed characteristics, which might affect children’s educational and child labour outcomes. Moreover, Houmark, Ronda and Rosholm (2024) show that failing to control for children's genes and giftedness, the effect of parental investment in education is often overestimated since parents tend to invest more in more gifted children. In our context, this implies that parents of gifted children might decide to migrate to afford educational expenses. Therefore, the negative effect of parental migration on average children's educational outcomes might be misleading. Accordingly, more research considering the use of different control groups is needed.

Overall, the collected systematic evidence calls policymakers of countries with high emigration and/or internal labour migration to be aware of the challenges faced by left behind children and to provide safety nets for children in the absence of their parents.

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Appendices

Appendix 1: Search strings

Search in Web of Science:

Concept 1: parental migration	((Parent* OR paternal OR maternal) NEAR/4 (migra* OR emigration)) OR (absen* NEAR/4 (mother* OR father* OR parent*)) OR "transnational migra" OR "internal migra*" OR "labo?r migra*" OR "migrant worker*" OR "international migra*" OR "stayer youth"
Concept 2: children left behind	((child* OR girl* OR boy* OR adolescent* OR youth OR family) NEAR/4 ("left behind" OR " left-behind")) OR "transnational famil*" OR "transnational household*"
Concept 3: educational and child labour outcomes	"child labo?r" OR "child* employ*" OR "years of education" OR "years of schooling" OR "school enrollment" OR "educational attainment" OR "educational trajectories" OR "level of education" OR "educational level" OR "learning outcomes "OR "educational outcomes" OR "child* development" OR "children's development" OR "child's development" OR "school performance" OR "academic achievement" OR "academic performance" OR "education" OR "academic engagement" OR "school engagement" OR "educational functioning" OR "educational problems" OR "school satisfaction" OR "in-school outcomes" OR "educational achievement" OR "school adjustment" OR ((academic) NEAR/4 (trajectories)) OR ((academic) NEAR/4 (well-being)) OR "secondary school" OR "pre-school" OR "children's cognitive development" OR “remittances” OR “human capital” OR “parental care”

Search in Scopus:

Concept 1: parental migration	((Parent* OR paternal OR maternal) w/4 (migra* OR emigration)) OR (absen* w/4 (mother* OR father* OR parent*)) OR "transnational migra" OR "internal migra*" OR "labo?r migra*" OR "migrant worker*" OR "international migra*" OR "stayer youth"
Concept 2: children left behind	((child* OR girl* OR boy* OR adolescent* OR youth OR family) w/4 ("left behind" OR " left-behind")) OR "transnational famil*" OR "transnational household*"
Concept 3: educational and child labour outcomes	"child labo?r" OR "child* employ*" OR "years of education" OR "years of schooling" OR "school enrollment" OR "educational attainment" OR "educational trajectories" OR "level of education"

	OR "educational level" OR "learning outcomes "OR "educational outcomes" OR "child* development" OR OR "children's development" OR "child's development" OR "school performance" OR "academic achievement" OR "academic performance" OR "education" OR "academic engagement" OR "school engagement" OR "educational functioning" OR "educational problems" OR "school satisfaction" OR "in-school outcome" OR "educational achievement" OR "school adjustment" OR ((academic) w/4 (trajectories)) OR ((academic) w/4 (well-being)) OR "secondary school" OR "pre-school" OR "children's cognitive development" OR "human capital " OR "remittances" OR "parental care"

Search in Google Scholar[1]:

Search for educational outcomes	allintext: "migration" AND "child" AND "left behind" AND "education*" OR "school*" OR "aspir*"
Search for child labour outcomes	allintext: "migration" AND "children left behind" OR "left behind children" AND "child labour" OR "child labor" OR "time allocation" OR "time use pattern"

[1] In Google Scholar, there is a character limit so the search string was adapted.

Appendix 2: All outcome variables considered in this study

Educational outcomes	Years of education, education expenditures, test scores (grades, math, English, Chinese, etc.), educational degree, educational disruption (lagging behind or dropped out), lagging behind, years lagging behind, drop out, cognitive test score, entered college, school progression, below average school performance, above average school performance, school achievement (positive class position, positive report), number of hours spent on school (like homework, additional reading) outside school hours
Child labour outcomes	Child labour dummy, hours worked, days worked per week, weeks worked

Appendix 3: Extensive explanation of the stopping rule

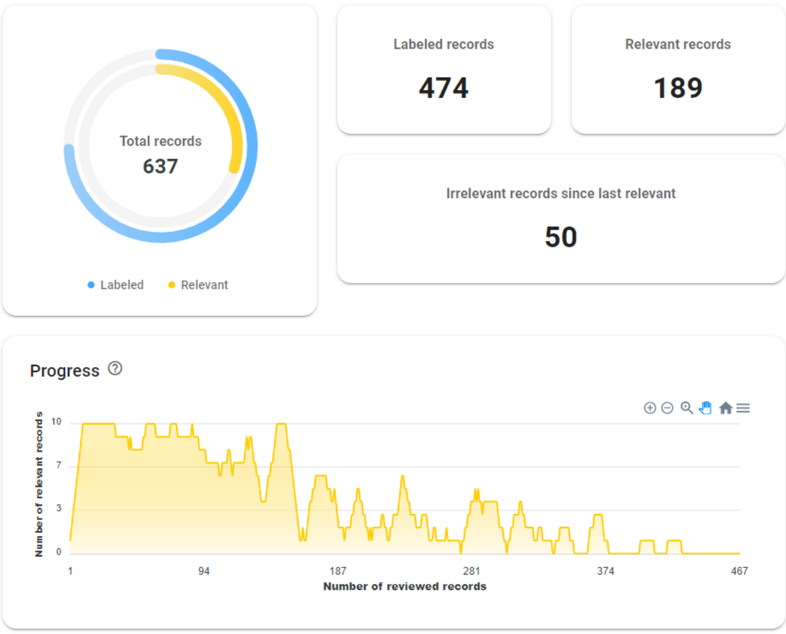
A stopping rule for *ASReview* was determined beforehand. When deciding for a stopping rule for reviewing articles in the *ASReview* environment, the main criteria is the adequacy of including all relevant papers and excluding all irrelevant papers. The golden standard for this process is human reviewers, who tend to have an average error rate of around 10% (Wang et al., 2020). This relates to both false negatives and false positives. Therefore, with the help of *ASReview*, we should identify at least 90% of all relevant papers correctly while saving time and resources as compared to reviewing manually. The most simplistic and commonly used stopping rule is to stop after a predefined number of irrelevant articles in a row, e.g. 50 (Ros, Bjarnason, & Runeson, 2017). However, this approach is not considered as best practice when used alone (Van Haastrecht et al., 2021; Yu & Menzies, 2019). According to Van Haastrecht et al. (2021, p. 5) the stopping rule can be based on the following formula instead, estimating the number of relevant papers based on the total amount of papers to be screened:

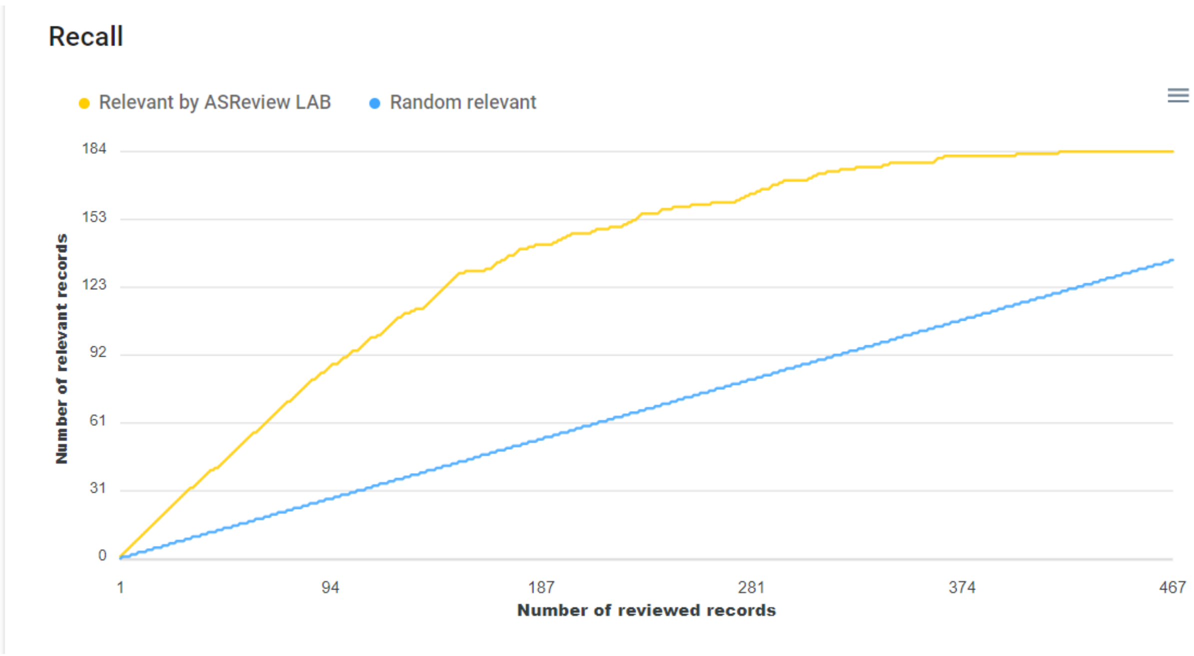
$$R \approx N \times \frac{r}{r+i}$$

with N being the total number of papers, r the number of papers labelled as relevant, i the number of papers labelled as irrelevant and R the total number of relevant papers, which is unknown. The proposed stopping rule is then to stop once a pre-defined percentage p of the estimated number of relevant papers R has been marked relevant (Van Haastrecht et al., 2021).

Following previous research using *ASReview*, a combination of these two methods is used in our paper (Ros, Bjarnason, & Runeson, 2017; van Dee, Schnack, & Cahn, 2023; Van Haastrecht et al., 2021). First, the formula by Van Haastrecht et al. (2021) is used to estimate the number of relevant papers in our paper set. According to the assessment of *ASReview* by Van De Schoot et al. (2021, p. 130), “95% of the eligible studies will be found after screening between only 8% to 33% of the studies.” Since our search resulted in 637 studies, 95% of the relevant studies should be found after screening 210 articles. Accordingly, we apply the formula of Van Haastrecht et al. (2021) at this point, resulting in a total of 448.9 (637 X 148/(148+62)) estimated relevant articles. Following the reasoning of van Haastrecht (2022) and previous research by van Dee, Schnack and Cahn (2023) and Bourke et al. (2023), screening is also stopped when 50 papers in a row are labelled irrelevant to prevent overestimating the number of relevant papers and screening inefficiently. It is common to stop screening after 50 consecutive irrelevant papers (Loheide-Niesmann, Riem, & Cima, 2022; Ros, Bjarnason, & Runeson, 2017; van Dee, Schnack, & Cahn, 2023). After reviewing 474 abstracts and titles, 50 papers in a row were deemed irrelevant and screening was stopped (see Appendix 4). At this point, 74.41% of the total articles were screened.

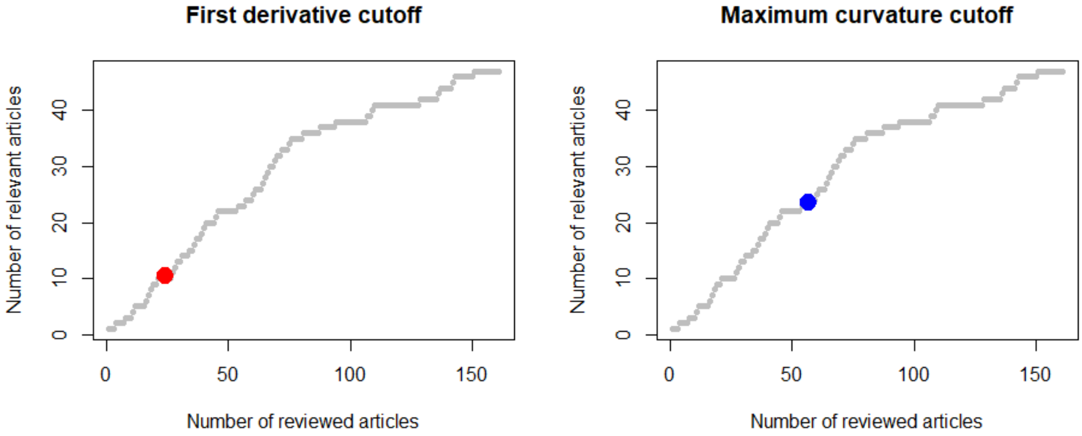
Appendix 4: ASReview analytics



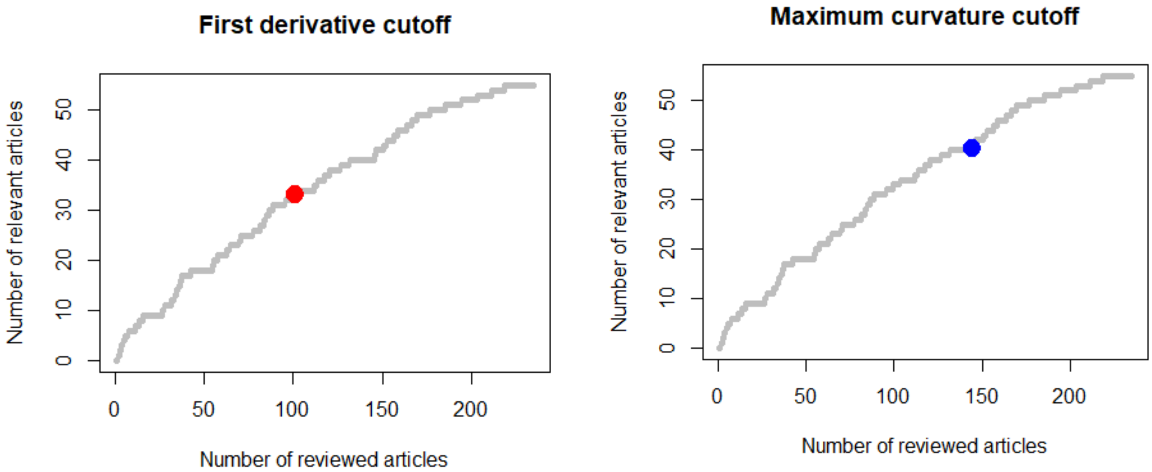


Appendix 5: Knee Method for Google Scholar

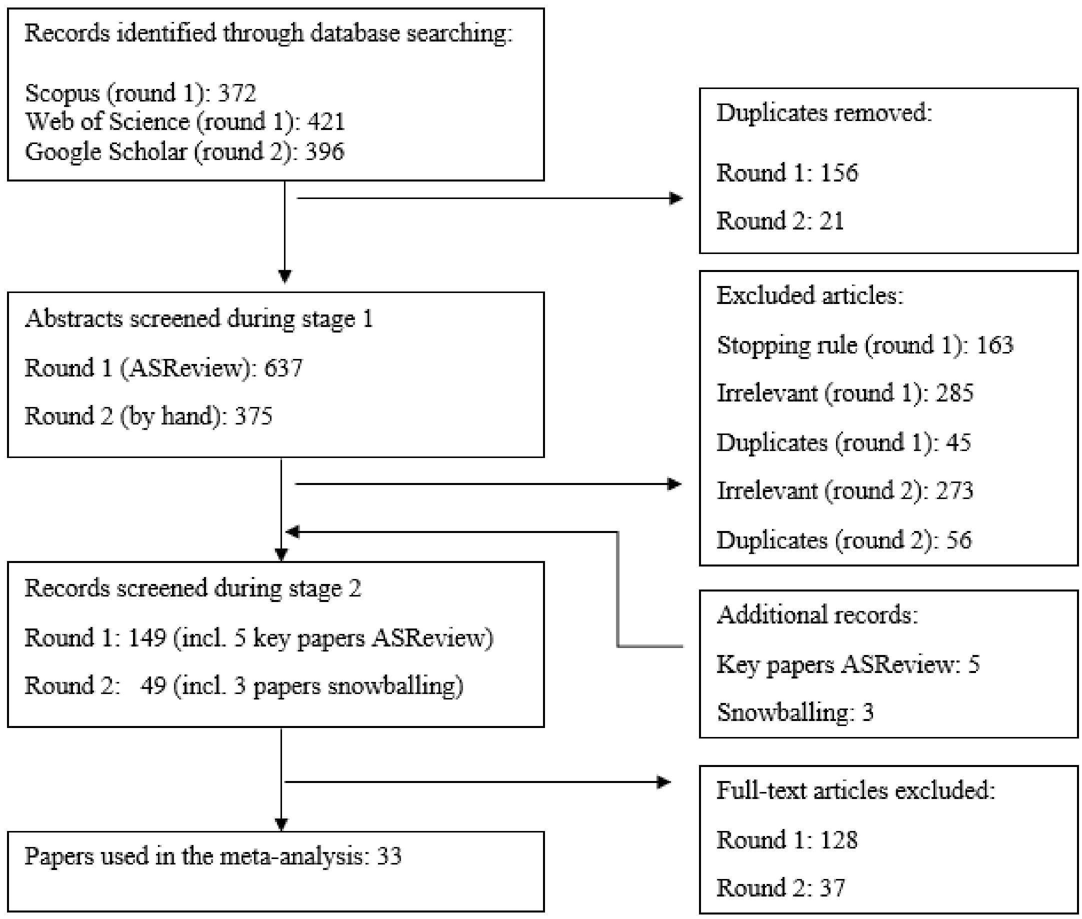
Knee method for educational outcomes



Knee method for child labour outcomes



Appendix 6: PRISMA diagram



Appendix 7: Breusch-Pagan test

P-value	Conclusion
Positive educational outcomes	
0.000	There may be study-level effects present, suggesting the need for a multilevel model
Negative educational outcomes	
0.518	No strong evidence for study-level effects based on this test
Child labour outcomes	
0.000	There may be study-level effects present, suggesting the need for a multilevel model

Appendix 8: I^2 statistics for every model specification including moderators

	Dependent variable: t value

	Fixed Effects (2)	Multilevel Random Effects (3)
Positive educational outcomes		
I^2	99.98%	99.98%
Negative educational outcomes		
I^2	100%	100%
Child labour outcomes		
I^2	99.99%	99.99%

Appendix 9: Regression test for funnel plot asymmetry

	b	p-value
Positive educational outcomes - REML		

0.015	<0.0001
Negative educational outcomes - FE	
-0.071	<0.0001
Child labour outcomes - REML	
-0.014	<0.0001

Appendix 10: Genuine effect and publication bias without clustered standard errors for every outcome category

	Dependent variable: t value		
	OLS (SE)	Fixed Effects (SE)	Multilevel Random Effects (SE)
	(1)	(2)	(3)
Positive educational outcomes			
Genuine effect (PET)	-0.512** (0.210)	0.121*** (0.003)	1.056* (0.572)
Bias (FAT)	0.015*** (0.004)	0.006*** (0.000)	-0.017** (0.007)
Observations		310	
Studies		18	
Negative educational outcomes			
Genuine effect (PET)	5.463*** (1.189)	7.540*** (0.008)	0.307 (3.690)
Bias (FAT)	-0.071*** (0.016)	-0.096*** (0.001)	0.002 (0.052)
Observations		46	
Studies		5	
Child labour outcomes			
Genuine effect (PET)	1.297*** (0.363)	3.394*** (0.004)	3.430*** (0.774)
Bias (FAT)	-0.014** (0.006)	-0.044*** (0.000)	-0.053*** (0.011)
Observations		221	
Studies		15	

Note: **p<0.1;* ***p<0.05;* ****p<0.01*

Appendix 11: Genuine effect and publication bias with country and decade-fixed effects

	Dependent variable: t-value	
	OLS (Clustered SE)	Multilevel Random Effects (Clustered SE)
	(1)	(2)
Positive educational outcome		
Genuine effect	-1.022** (0.494)	-0.156 (1.885)
Bias	-0.013 (0.015)	-0.017 (0.031)
Burkina Faso	7.685*** (0.769)	8.025** (1.850)
El Salvador	1.757*** (0.518)	1.719* (0.740)
India	2.457*** (0.875)	2.767 (1.979)
Kenya	3.823*** (0.313)	4.027*** (0.823)
Nepal	-1.389 (0.926)	-1.258 (1.714)
Philippines	0.736** (0.286)	0.845** (0.420)
Romania	0.898 (0.612)	0.971 (1.199)
Senegal	6.728*** (0.635)	7.031** (1.563)
Tajikistan	1.572** (0.619)	1.871 (1.528)
1990	1.876*** (0.332)	0.240 (1.499)
2000	1.522*** (0.412)	0.631 (1.492)
2010	0.932 (0.637)	0.281 (1.452)
Observations	310	
Child labour outcomes		
Genuine effect	9.545 (6.974)	9.908 (15.209)
Bias	-0.102 (0.074)	-0.106 (0.162)
Burkina Faso	-1.415*** (0.410)	-0.791 (1.838)
El Salvador	-0.672 (1.072)	-0.106 (2.344)
India	1.205 (0.755)	1.660 (2.337)
Kenya	6.033* (3.398)	6.826 (8.056)
Nepal	4.572 (2.897)	5.283 (6.972)
Philippines	4.939 (4.495)	5.790 (10.421)
Romania	-3.304 (2.347)	-3.256 (4.401)
Senegal	-1.068 (1.595)	-1.321 (4.213)
Tajikistan	-7.250 (5.257)	-8.084 (12.079)
1990	-5.095 (4.101)	-5.924 (9.571)
2000	9.545 (6.974)	-0.106 (0.162)
2010	-0.102 (0.074)	-0.791 (1.838)
Observations	221	

*Note: *p<0.1; **p<0.05; ***p<0.01. The reference country is China and the reference decade is 1980.*

Appendix 12: Multivariate analysis for positive educational outcomes

	Dependent variable: t-value		
	OLS (Clustered SE)	Fixed Effects (SE)	Multilevel Random Effects (SE)
	(1)	(2)	(3)
Positive educational outcomes			

Genuine effect	-2.013** (0.790)	-2.175*** (0.008)	-2.013*** (0.636)
Bias	-0.010 (0.007)	-0.016*** (0.0001)	-0.010* (0.005)
Other method	-0.375* (0.210)	-0.533*** (0.004)	-0.375 (0.249)
Fixed effects regression	-0.964*** (0.241)	-1.095*** (0.004)	-0.964*** (0.236)
Quasi-experimental	-2.124*** (0.519)	-2.457*** (0.011)	-2.124** (0.861)
Age sample	2.081*** (0.683)	2.372*** (0.007)	2.081*** (0.610)
Father	1.260*** (0.341)	1.878*** (0.005)	1.261*** (0.265)
Mother	0.105 (0.170)	0.569*** (0.006)	0.105 (0.291)
Girls	-0.572 (0.407)	-1.225*** (0.004)	-0.572** (0.285)
Boys	-0.795*** (0.252)	-0.676*** (0.005)	-0.795*** (0.289)
Regional or district fixed effects	1.610*** (0.252)	1.663*** (0.005)	1.610*** (0.356)
Education of the household head	5.620*** (0.513)	6.636*** (0.009)	5.620*** (0.715)
Wealth	0.631* (0.352)	1.259*** (0.005)	0.631** (0.315)
Interaction term	-1.636** (0.821)	-1.679*** (0.006)	-1.636*** (0.505)
Number of children in the family	-1.335*** (0.265)	-1.332*** (0.004)	-1.335*** (0.288)
Google Scholar citations weighted by publication age	-0.637*** (0.205)	-0.462*** (0.003)	-0.637*** (0.200)
Observations		258	

*Note: *p<0.1; **p<0.05; ***p<0.01. Clustered standard errors could not be calculated for the fixed effects and multilevel random effects model because of the limited number of observations in combination with the amount of moderators included.*

Appendix 13: Multivariate analysis for negative educational outcomes

	Dependent variable: t-value		
	OLS (Clustered SE)	Fixed Effects (SE)	Multilevel Random Effects (SE)
	(1)	(2)	(3)
Negative educational outcomes			
Genuine effect	8.056*** (0.330)	7.958*** (0.008)	8.056*** (1.207)
Bias	-0.101*** (0.005)	-0.106*** (0.0001)	-0.101*** (0.016)
Girls	-5.090*** (0.151)	-5.343*** (0.022)	-5.090*** (1.742)
Boys	-5.816*** (0.153)	-6.072*** (0.022)	-5.816*** (1.744)
Observations		46	

*Note: *p<0.1; **p<0.05; ***p<0.01*

Appendix 14: Multivariate analysis for child labour outcomes

	Dependent variable: t-value		
	OLS (Clustered SE)	Fixed Effects (Clustered SE)	Multilevel Random Effects (Clustered SE)
	(1)	(2)	(3)
Child labour outcomes			
Genuine effect	3.966*** (0.612)	3.343** (0.950)	3.709*** (0.758)
Bias	-0.036*** (0.004)	-0.032*** (0.008)	-0.034*** (0.007)
IV	0.815*** (0.196)	1.119*** (0.324)	0.889*** (0.325)
Quasi-experimental	-2.086*** (0.635)	-1.927** (0.861)	-2.011** (0.921)
Girls	-1.144*** (0.374)	-0.789 (0.566)	-1.110** (0.530)
Boys	-0.613* (0.313)	-0.243 (0.438)	-0.600 (0.436)
Google Scholar citations weighted by publication age	0.478*** (0.078)	0.516*** (0.088)	0.433*** (0.117)
Observations		137	

Note: *$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$*

Appendix 15: Immediate vs long-term effect subsamples multivariate analysis

	Dependent variable: t-value		
	OLS (Clustered SE)	Fixed Effects (SE)	Multilevel Random Effects (SE)
	(1)	(2)	(3)
Immediate effects			
Positive educational outcomes			
Genuine effect	0.380 (0.696)	0.192*** (0.025)	0.402 (1.265)
Bias	-0.033 (0.025)	-0.011*** (0.000)	-0.033 (0.048)
Observations	31	31	31
Long term effects			
Positive educational outcomes			
Genuine effect	1.138*** (0.337)	1.407*** (0.027)	1.138 (1.206)
Bias	-0.020*** (0.004)	-0.022** (0.000)	-0.020 (0.016)
Observations	81	81	81

*Note: *p<0.1; **p<0.05; ***p<0.01. Clustered standard errors could not be calculated for the fixed effects and multilevel random effects model because of the limited number of observations in combination with the number of moderators included. The subsample analysis was not possible for child labour outcomes since there were no long-term observations and the distinction between short-term and long-term child labour outcomes is also not practically meaningful. All models for positive educational outcomes control for the following variables: Other method, Fixed effects regression, Father, Mother, Regional/District fixed effects, Wealth, Interaction term, Number of children in the family and Google Scholar citations weighted by publication age.*

Appendix 16: China subsample multivariate analysis

	Dependent variable: t-value		
	OLS (Clustered SE)	Fixed Effects (SE)	Multilevel Random Effects (SE)

	(1)	(2)	(3)
China			
Positive educational outcomes			
Genuine effect	0.756* (0.443)	1.037*** (0.030)	0.0756 (1.412)
Bias	-0.024** (0.011)	-0.034*** (0.0002)	-0.024*** (0.009)
Observations	174	174	174
Child labour outcomes			
Genuine effect	-1.137*** (0.326)	-1.374*** (0.031)	-1.137 (4.510)
Bias	0.012*** (0.003)	0.014*** (0.000)	0.012 (0.043)
Observations	48	48	48
Other countries			
Positive educational outcomes			
Genuine effect	-4.453*** (1.343)	-3.930*** (0.023)	-3.066*** (1.134)
Bias	0.044 (0.029)	0.071*** (0.0003)	0.065*** (0.020)
Observations	84	84	84
Child labour outcomes			
Genuine effect	5.222*** (0.843)	4.357*** (0.013)	3.814*** (1.261)
Bias	-0.042*** (0.004)	-0.039*** (0.000)	-0.031*** (0.010)
Observations	89	89	89

*Note: *p<0.1; **p<0.05; ***p<0.01. Clustered standard errors could not be calculated for the fixed effects and multilevel random effects model because of the limited number of observations and the number of moderators included. All models for positive educational outcomes control for the following variables: Other method, Fixed effects regression, Age sample, Father, Mother, Girls, Boys, Regional or district fixed effects, Education of the household head, Wealth, Interaction term, Number of children in the family, Google Scholar citations weighted by publication age. All models for child labour outcomes control for IV, Quasi-experimental, Girls, Boys and Google Scholar citations weighted by publication age.*

Appendix 17: Country-income subsamples multivariate analysis

	Dependent variable: t-value		
	OLS (Clustered SE)	Fixed Effects (SE)	Multilevel Random Effects (SE)
	(1)	(2)	(3)
Low-income countries			

Positive educational outcomes			
Genuine effect	-2.398 (1.668)	-1.602*** (0.011)	1.867 (2.063)
Bias	0.014 (0.025)	-0.006*** (0.000)	-0.035** (0.016)
Observations	113	113	113
Child labour outcomes			
Genuine effect	1.437*** (0.018)	1.401*** (0.012)	3.672 (4.131)
Bias	-0.014*** (0.000)	-0.014*** (0.000)	-0.039 (0.046)
Observations	61	61	61
Lower-middle income countries			
Positive educational outcomes			
Genuine effect	-0.163 (1.166)	-1.452*** (0.021)	-0.841 (1.487)
Bias	-0.013 (0.025)	0.012*** (0.000)	0.005 (0.024)
Observations	107	107	107
Child labour outcomes			
Genuine effect	6.289 (4.307)	16.988*** (0.013)	3.250 (4.278)
Bias	-0.087* (0.051)	-0.173*** (0.000)	-0.030** (0.044)
Observations	77	77	44
Upper-middle income countries			
Positive educational outcomes			
Genuine effect	0.542* (0.279)	0.651*** (0.035)	0.542 (0.983)
Bias	-0.032*** (0.005)	-0.025***(0.001)	-0.032 (0.020)
Observations	38	38	38
Child labour outcomes			
Genuine effect	-1.017*** (0.296)	-0.527*** (0.013)	-1.340 (1.316)
Bias	0.041*** (0.011)	0.028*** (0.000)	0.033 (0.020)
Observations	83	83	29

*Note: *p<0.1; **p<0.05; ***p<0.01. Clustered standard errors could not be calculated for the fixed effects and multilevel random effects model because of the limited number of observations and the number of moderators included. All models for positive educational outcomes control for the following variables: Other method, Fixed effects regression, Father, Mother, Girls, Boys, and Google Scholar citations weighted by publication age. All models for child labour outcomes control for the following variables: IV, Quasi-experimental, Girls, Boys and Google Scholar citations weighted by publication age.*

Appendix 18: Types of child labour subsamples multivariate analysis

	Dependent variable: t-value		
	OLS (Clustered SE)	Fixed Effects (SE)	Multilevel Random Effects (SE)
	(1)	(2)	(3)
Unpaid domestic work			
Genuine effect	4.430*** (0.423)	3.890*** (0.025)	4.430*** (1.492)
Bias	-0.047*** (0.005)	-0.042*** (0.000)	-0.047*** (0.015)
Observations	30	30	30

Unpaid farm work			
Genuine effect	1.591 (1.016)	0.189*** (0.030)	1.591 (2.520)
Bias	-0.009 (0.009)	0.002*** (0.000)	-0.009 (0.025)
Observations	17	17	17
Paid work			
Genuine effect	-4.702*** (0.066)	-5.005***(0.023)	-4.702 (2.703)
Bias	0.076*** (0.012)	0.084*** (0.0003)	0.077 (0.050)
Observations	22	22	22
Unspecified work			
Genuine effect	3.465*** (1.065)	3.056*** (0.023)	4.350** (1.890)
Bias	-0.028*** (0.003)	-0.030*** (0.000)	-0.032*** (0.010)
Observations	60	60	60

*Note: *p<0.1; **p<0.05; ***p<0.01. Clustered standard errors could not be calculated for the fixed effects and multilevel random effects model because of the limited number of observations and the number of moderators included. The models estimating unpaid and unspecified work control for the following variables: IV, Girls, Boys, and Google Scholar citations weighted by publication age. The model that estimates paid work controls for the following variables: IV, Girls and Boys.*

Appendix 19: Intensive versus extensive margin subsamples multivariate analysis

	Dependent variable: t-value		
	OLS (Clustered SE)	Fixed Effects (SE)	Multilevel Random Effects (SE)
	(1)	(2)	(3)
Intensive margin			
Positive educational outcomes			
Genuine effect	-2.539*** (0.540)	-2.105*** (0.011)	-2.539** (1.169)
Bias	-0.018*** (0.007)	-0.025*** (0.000)	-0.018** (0.008)
Observations	180	180	180
Child labour outcomes			
Genuine effect	4.457*** (0.432)	3.981*** (0.022)	4.457*** (1.085)
Bias	-0.023*** (0.005)	-0.019***(0.000)	-0.023 (0.014)
Observations	86	86	86
Extensive margin			
Positive educational outcomes			
Genuine effect	-7.338*** (1.412)	-8.246*** (0.20)	-4.383** (1.847)
Bias	0.114*** (0.024)	0.102*** (0.000)	0.074*** (0.016)
Observations	78	78	78
Child labour outcomes			
Genuine effect	-2.557*** (0.539)	0.676*** (0.019)	0.778 (2.330)
Bias	-0.018*** (0.007)	-0.007*** (0.000)	-0.008** (0.022)
Observations	50	50	50

*Note: *p<0.1; **p<0.05; ***p<0.01. Clustered standard errors could not be calculated for the fixed effects and multilevel random effects model because of the limited number of observations and the number of moderators included. All models for positive educational outcomes control for the following variables: Other method, Fixed effects regression, Quasi-experimental, Age sample, Father, Mother, Girls, Boys, Region/District Fixed effects, Wealth, Number of children and Google Scholar citations weighted by publication age. All models for child labour outcomes control for the following variables: IV, Quasi-experimental, Girls, Boys and Google Scholar citations weighted by publication age.*

Appendix 20: Peer-reviewed subsample multivariate analysis

	Dependent variable: t-value

	OLS (Clustered SE)	Fixed Effects (SE)	Multilevel Random Effects (SE)
	(1)	(2)	(3)
Peer reviewed			
Positive educational outcomes			
Genuine effect	-0.911 (0.581)	-0.757*** (0.004)	0.502 (0.672)
Bias	0.015 (0.015)	0.007*** (0.000)	0.001 (0.008)
Observations	252	252	252
Child labour outcomes			
Genuine effect	0.858 (0.987)	0.033*** (0.013)	0.858 (0.934)
Bias	-0.007 (0.009)	0.001*** (0.000)	-0.007 (0.010)
Observations	69	69	69
Not peer reviewed			
Positive educational outcomes			
Genuine effect	1.063** (0.461)	0.675*** (0.044)	1.062 (1.130)
Bias	-0.034 (0.021)	-0.014*** (0.002)	-0.034 (0.043)
Observations	58	58	58
Child labour outcomes			
Genuine effect	2.744*** (0.520)	3.001*** (0.016)	2.745*** (0.818)
Bias	-0.032 (0.004)	-0.035*** (0.000)	-0.032*** (0.005)
Observations	65	65	65

Notes: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Clustered standard errors could not be calculated for the fixed effects and multilevel random effects model because of the limited number of observations and the number of moderators included. All models for positive educational outcomes control for the following variables: Other method, Fixed effects regression, Father, Mother and Interaction term. All models for child labour outcomes control for the following variables: IV, Girls, Boys and Google Scholar citations weighted by publication age.