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Constellations of risk factors as moderators of the impact of a randomized intervention on students' reading skills in rural India

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ABSTRACT

Individual, family and community risk factors might determine the success or failure of educational interventions. The study is a secondary analysis, aimed at identifying distinctive constellations of risk for educational attainment, and at exploring whether membership to these constellations moderated the impact of a cluster-randomized reading intervention in rural India. By means of latent profile analysis, four constellations of risk were identified based on individual and family risk-factors. Multilevel cumulative logit models confirmed that the intervention had a positive impact on the outcome, and revealed that profile membership did not moderate the effect of the intervention. However more nuanced analysis showed that the intervention worked differently for children with different risk-profiles depending on contextual factors.

1. Introduction

The ability to read is one of the most fundamental building stones of human capital and lifelong learning. Literacy predicts, among others, individuals' health, higher wages and financial knowledge outcomes (World Bank, 2018; Valerio, Puerta, Tognatta, & Monroy-Taborda, 2016), and is historically associated with countries' reduction of violence, distribution of income, and economic growth (World Bank, 2018). As part of the Global Goals for Sustainable Development set by the United Nations, literacy has long been a target of intervention programs that aim at reducing educational inequalities, particularly in low- and middle-income countries (L&MICs)—including India, the focused country in this study. While interventions have been associated with improvements in educational access, learning outcomes of students in L&MICs are still deficient. Data about the progress of the Sustainable Development Goals in Central and South Asia indicates that about 75% of students enrolled in schools are not reaching minimum reading proficiency levels (UNESCO Institute for Statistics (UIS) and Global Education Monitoring Report (GEMR), 2017)).

One factor that could partially explain the (in)efficacy of reading interventions in L&MICs is individual, family and community risk. The effects of interventions on educational outcomes are known to fluctuate across contexts and participant characteristics (Duncan & Vandell, 2012; Weiss, Bloom, & Brock, 2014), with the latter representing the main source of variation (Coffield, 2012; Snijders & Bosker, 2012). Individual and family characteristics are here conceived as risk/protective factors for educational success, which might also be reinforced

or buffered by community characteristics. Since it is known that risk factors tend not to occur in isolation (Cicchetti & Rogosch, 1996; Sameroff & Seifer, 1983), nor to operate only at the individual or family level (Hasselhorn et al., 2014), risk is operationalized as “constellations”. Constellations of risk may better explain the interaction of an individual with his/her environment, providing more comprehensive insights into differential impacts of interventions (Cooper & Lanza, 2014).

This study is a secondary analysis of the Pratham Information Project implemented in Jaunpur, a rural district in Uttar Pradesh state, India, which aimed to increase students' reading ability by fostering villagers' participation in education (Banerjee, Banerji, Duflo, Glennerster, & Khemani, 2010). One of the variations of this intervention was successful in improving students' reading performance, although not by means of the theorized path of effects (i.e., by increasing citizens' participation in education). The current study is aimed at better understanding the conditions under which this intervention worked. Therefore, it is explored a) whether students with different constellations of risk factors at baseline differentially responded to the intervention, and b) whether student and community risk factors interact with each other to facilitate or hinder the effects of the intervention. Findings will add to the understanding of the effects of multiple risks on educational attainment by exploring the case of rural India. In addition, the person-oriented approach to risk will expand the literature on cumulative risk as moderator of intervention effects.

The rest of this section is organized as follows. First, the issue of risk is addressed, both at the individual and family level, and at the

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community level, with emphasis on the case of rural India; second, a brief review of efforts to improve literacy outcomes in L&MICS is presented, followed by a description of the original Pratham Information Project and findings from its impact evaluation; third, the aims and research questions addressed by this study are introduced.

1.1. Multiple risk: individual/family and community factors

Multiple risk supposes that the occurrence of one risk factor in the presence of others, impacts development in a different manner than each one independently (Cicchetti & Rogosch, 1996). Multiple risk addresses both the co-existence of different risk-factors within a child, and their multilevel allocation (Hasselhorn et al., 2014). Longitudinal studies have shown that children who present multiple risk factors tend to score lower in developmental and educational outcomes than children with single risks (Gutman, Sameroff, & Cole, 2003; Appleyard, Egeland, van Dulmen, & Sroufe, 2005; Burchinal, Roberts, Hooper, & Zeisel, 2000; Rouse & Fantuzzo, 2009). A particularly strong cumulative effect of multiple risks has been found in the development of reading skills in young children (Rouse & Fantuzzo, 2009). Moreover, both *type* of risk and the *amount* of it have been found to hold unique effects on educational outcomes (Rouse & Fantuzzo, 2009), therefore analytical approaches that shed light on the interplay of both are desired.

The following sections will review the individual and family dimensions that will compose the empirical risk constellations in the current study. It does not intend to be an exhaustive list of risk factors for educational failure, but it tries to review factors that are particularly relevant for the region—Northern, rural India—and the specific context of the study.

1.1.1. Gender

While educational gender gaps in Western countries have been reversed in the past 25 years (DiPrete & Buchmann, 2013), the situation is different in India. India ranks 126 out of 142 countries in the index for female educational attainment, with female-to-male ratios of 0.68 for literacy, and 0.79 for secondary school enrolment (World Economic Forum, 2014). The gender gap in India has been associated with culturally embedded values and practices that persist in spite of the country's economic growth (Jayachandran, 2014). In India—and particularly in Northern India, the region concerned in this paper—there is a pervasive son preference, which has been attributed to the fact that girls belong to the family of origin only until marriage, resulting in less incentives for families to invest on their daughters' education (Bose, 2012; Lin & Adserà, 2013). Son preference has also been associated with significant differences in the hours of housework performed by school-aged girls (ages 6–14), as compared to their male peers (Lin & Adserà, 2013). These practices change slowly and dissimilarly across the country, as reflected by intergenerational analyses that indicate that women's educational mobility has improved in India, but only in urban areas (Emran & Shilpi, 2012). Therefore, female students in rural India can be considered at a higher risk for educational delays and dropout than their male counterparts.

1.1.2. Parental education

The association between parental education and children's academic success has been documented profusely (e.g., Feinstein, Duckworth, & Sabates, 2004; Hasselhorn et al., 2014; Moore, Vandivere, & Anderson, 2006). Feinstein et al. (2004) argue that there are several pathways for the inter-generational effect of parental education on their offspring's educational attainment. These pathways are summarized in indirect and moderating effects, and are related to distal and proximal processes of development (Bronfenbrenner & Morris, 2006). One of the indirect pathways posits that parental education has impact on distal characteristics of the family environment, such as its structure, employment and poverty situation. At a more proximal level,

parental education shapes parental beliefs, influences mental and physical health, and determines the availability of educational materials and resources. Finally, parental education is thought to influence the quality of the home interactions, parenting style and educational practices children are exposed to, which are considered the factor that most directly determines educational attainment. In addition, parental education is considered a potential moderator of each of these processes, eventually buffering the risks faced at each of these levels.

1.1.3. Previous skill level

The statement “skill begets skill” (Heckman, 2000, p. 50) summarizes the idea that educational attainment is a cumulative process, in which later stages build dynamically on earlier stages. Educational systems are in fact built upon a cumulative advantage model, which requires students to master a previous level before being able to continue to later stages (DiPrete & Eirich, 2006). Early advantage, therefore, leads to later better outcomes. The well-known *Matthew effect* (Walberg & Tsai, 1983) describes this educational phenomenon. Explanations for this mechanism posit that previous attainment predicts motivation and learning behavior, and all these three have a cumulative effect on later achievement (Walberg & Tsai, 1983). In the case of reading skills, low ability readers have been and will continue to be less exposed to print material than more skillful readers, which widens the gap between these two groups (Alexander, Schallert, & Reynolds, 2009; Mol & Bus, 2011).

1.1.4. School absenteeism

Stable school absenteeism and dropout is both a result and a precursor of risk for educational failure. Low parental education and involvement, poverty, homelessness, school victimization, child or adolescent employment, psychological problems, and family conflict have been identified as some of the main precursors of school absenteeism (Kearney, 2008; Nair, 2010; Ready, 2010; Rouse & Fantuzzo, 2009). While most of the research has been conducted in the English-speaking world, a review study by Kearney (2008) confirms similar predictors of absenteeism in other countries—including India. As a risk-factor, absenteeism has been linked to future school dropout, delinquency, psychological disorders, low employment, and economic difficulties (Kearney, 2008; Nair, 2010). The risk for school dropout deserves particular attention in the context of rural India, where the proportion of not-enrolled children in school age reaches 43.8% for girls and 14.6% for boys in four rural states—including Uttar Pradesh (Drèze & Kingdon, 2001).

1.1.5. Family size

Family size has been conceptualized as a mediator of the relationship between family and social characteristics and the child's competence (Sameroff & Seifer, 1983). Large family size—4 or more children—has been found to be related to higher risk for psychological and behavioral problems, and to an increased chance of being expelled or suspended from school (Moore et al., 2006). Some research findings suggest that the effect of family size on children's education may be actually masking birth order effects (Black et al., 2015; De Haan, 2010). However, evidence from India indicates that there are unique detrimental associations of family size on children's schooling, and that these links are particularly negative in the case of first-born children, and females (Bhat, 2002). These children are more likely to withdraw from school to either work or take care of younger siblings.

1.1.6. Parental knowledge of student's attainment

Although not defined as such in the literature, the accuracy of parent's knowledge about his/her child's attainment may be partially reflecting factors so relevant as parental involvement and expectations, constructs that have been extensively related to student school attainment (for a meta-analysis see Fan & Chen, 2001). Parents' perception of student academic skills has been regarded as a factor that can

contribute to explain student achievement. In general, parental attributions of their children's skills are communicated to the child, potentially influencing their own perception of ability, motivation, and achievement (Furnham & Akande, 2004). The accuracy of this perception has been shown to vary across cultures, to differ for boys and girls, and to depend on the parents' own educational level (Furnham & Akande, 2004; Furnham, Reeves, & Budhani, 2002; Furnham, Mkhize, & Mndaweni, 2004; Phillipson & Phillipson, 2007). There are two ways in which parental estimation of child's attainment could be conceptualized as a risk factor, and both of them could be representing a proxy for lack of parental monitoring in the child's educational activity: parents declaring not to know what the skill of his/her child is, or parents having particularly inaccurate estimations of their child's attainment—taking as norm the actual test scores of a child.

1.1.7. Community risk

Although the characteristics of the community are considered distal factors to individual development, risks at this level are expected to affect developmental outcomes mainly through their influence on the child's proximal environment (Bronfenbrenner & Morris, 2006). Key characteristics of neighborhoods may resemble—at a different level—the key characteristics of more proximal environments, such as levels of education, poverty, and beliefs about education (Feinstein et al., 2004). Indeed, characteristics of communities such as poverty can have a detrimental influence on the quality of relationships and support systems, which affects child development above and beyond family poverty (Feinstein et al., 2004; Yoshikawa, Aber, & Beardslee, 2012). The pathways of effect of community characteristics on individuals' outcomes may be indirect through the characteristics of more proximal environments, for example, by changing levels of family stress which in its turn affects family processes (Feinstein et al., 2004). Direct effects are possible, for example in the composition of peer groups, a factor that has been linked to outcomes such as school dropout (Feinstein et al., 2004).

In the case of India, research shows that women's education at the community level is associated with the strength of son preference in the community (Bose, 2012). This means that communities with more educated women tend to have more egalitarian gender practices. Moreover, research on inter-generational educational mobility describes different effects for women in urban and rural areas, and also distinguishes unique effects of neighborhoods on inequalities (Emran & Shilpi, 2012). Also levels of school participation have been shown to vary strongly across communities, with particularly low levels of participation in rural regions such as the one that concerns this study (Drèze & Kingdon, 2001).

1.1.8. Age and risk

Time, and therefore, age are obviously and intrinsically linked to learning and development. The cumulative character of learning, and age-related neurological and biological transformations, imply that older individuals have a natural advantage over younger ones in the mastery of certain skills, such as reading (Alexander et al., 2009). The schooling system is a key factor in reinforcing this advantage, as it exposes students to increasingly complex learning opportunities and it requires learners to master a certain level in order to move to more advanced stages (DiPrete & Eirich, 2006). However, the relation between age and learning is not linear. For example, evidence about relative age effects suggest that in the start of the school trajectory older students have an advantage over younger ones, but that this association weakens and even reverses in later school years (Navarro, García-Rubio, & Olivares, 2015; Thoren, Heinig, & Brunner, 2016; Verachtert, De Fraigne, Onghena, & Ghesquière, 2010). In addition, research in grade retention suggests that—over and above other predictors of academic achievement—there is little to no advantage to being older within a cohort of students, both in the early grades (e.g., Jaekel, Strauss, Johnson, Gilmore, & Wolke, 2015) and in high school (Martin,

2009). In sum, age is a crucial factor in explaining reading proficiency, but contrasting evidence suggests that it cannot be inarguably considered a protective or a risk factor for academic success (Morrison, Alberts, & Griffith, 1997).

1.2. Improving reading proficiency: the Pratham information project

Improving academic outcomes of school children in developing countries has been target of numerous interventions. Review and meta-analytic studies have tried to summarize the effectiveness of such interventions, distinguishing the levels where they intervene—from direct child interventions to community interventions (e.g., Snilstveit et al., 2015)—and linked to this, the theories of change that support them—(e.g., Ganimian & Murnane, 2016). A thorough examination of the effectiveness of different types of interventions on learning outcomes is out of the scope of this paper. However, there are two main insights from the extant literature that are particularly relevant in the context of the present study. First, evidence about the effectiveness of interventions suggests that the programs that are most effective in improving learning outcomes are those that create significant changes in children's daily school experiences (Ganimian & Murnane, 2016), and improve the match between teaching and student learning needs (Evans & Popova, 2016). In particular, language learning outcomes are best and more consistently improved by school interventions that make changes in pedagogical resources and content, including short teacher training to deliver new content (Snilstveit et al., 2015).

Second, evidence about the effectiveness of community based interventions on learning outcomes, such as the Pratham Information Project, suggests that there are important limitations to this approach. The theory of action behind these programs is that of social accountability, which implies that empowering communities with information and with an active role in monitoring the delivery of services—such as education—the quality of those services will increase (Snilstveit et al., 2015). Research indicates that interventions that provide information to communities about educational services and opportunities to participate, might lead to changes in intermediate outcomes (e.g., increased teacher attendance), but are not powerful in improving learning outcomes (Ganimian & Murnane, 2016). Moreover, these interventions might be more sensitive to differences in communities' social capital, and do not immediately address the quality of education, which is the most direct mechanism to boost student outcomes (Snilstveit et al., 2015).

The Pratham Information Project (Banerjee et al., 2010) is one of such programs. It was implemented in villages of the rural district of Jaunpur, state of Uttar Pradesh, India, with the aim of increasing the villagers' participation in local education. The hypotheses behind the program indicated that for community participation to increase, the villagers require a) information about the educational services and participation possibilities; b) tools to monitor learning outcomes; and c) concrete possibilities to be actively involved in improving learning outcomes of students. In order to test these hypotheses, a randomized intervention was developed, with villages as units of randomization. Three treatments—plus a control condition—were deployed, each of them tackling one of the hypotheses. They were developed in such a way that the most complex intervention—“Intervention 3”—comprised all activities delivered in interventions 1 and 2, plus a concrete opportunity for villagers to participate in improving learning of school-age children in the village. Hence, in intervention 3, groups of villagers first volunteered to be trained in pedagogical techniques to improve reading skills, and then provided reading camps for children in the village. The reading camps correspond to daily after-school reading classes held for two to three months. The classes followed the methodology used in Pratham's “Read India” program—thoroughly described by Banerji and Chavan (2016)—which has a mixed approach to language learning, combining phonics and whole-language methods. The method is articulated around the goal of reading with understanding,

and it uses a simple assessment tool—developed also by Pratham—to determine the initial level and to monitor those goals. The lessons include activities such as read-alouds and discussions, word games, mind mapping and free writing, as well as the introduction of a modernized version of a phonetic chart that is traditionally used in India for learning to write. In these camps, children are split into ability groups, and they move to a different group as they make progress in their learning.

Although the theory of change behind the Pratham Information Project assumed that the different degrees of information and possibilities for participation would lead to increased community involvement and school performance, the intervention shows other mechanism of action. In line with the meta-analytic evidence previously discussed, the only intervention that had significant impacts on children's learning outcomes (i.e., reading skills) was the one that changed children's daily learning experiences. The authors confirm that it is safe to assume that the impact of intervention 3 is fully attributable to attending the reading camps (Banerjee et al., 2010). Exploring whether the effect of reading camps is moderated by individual, family and community risk factors is still an open question, which will be the focus of the secondary analyses performed in the context of this study.

1.3. The current study

The current study corresponds to a secondary analysis of data collected in the context of the Pratham Information Project. In the light of evidence that intervention effects may vary across individuals with diverse characteristics, the present study attempts to investigate variation of program impacts in the Pratham Information Project, with focus on intervention 3 (compared against control villages). The main hypothesis is that children who are exposed to different risks—as measured at baseline—may profit from the intervention differently, and may interact differently with other contextual factors. Given that several risk factors are likely to coexist within one child, we use latent class analysis to identify recurrent constellations of individual and family risk in the sample. Typical constellations of risk may better account for the interaction between the individual and the exposure to the intervention (Cooper & Lanza, 2014).

The research questions guiding the study are the following: a) *What constellations of risk better describe the sample under study?* This question entails the identification of subgroups of children, or profiles, that represent distinct constellations of risk; b) *Does the child's membership into one of these profiles moderate the effect of the intervention on reading skills?* It is expected that depending on the constellations of risk, children reacted to the intervention differently. Possible effects are a (partial) compensatory effect of the intervention on subgroups of higher/more varied risk, or that children with initial advantages capitalize on these, increasing the gap with children of more disadvantaged profiles; and c) *Does child membership to one profile interact with other child and relevant village characteristics in moderating the effect of the intervention on reading skills?* It is expected that the potential moderation effect of profiles will differ depending on village characteristics. Given the wide age range, it is also expected that the association of profile membership and outcomes might depend on students' age.

2. Method

2.1. Sample

The Pratham Information Project randomly selected four blocks—an administrative unit, each of them containing around 100 villages—of the Jaunpur district. Within these blocks, villages were randomly selected to make the study representative of the district. A total of 17,533 children between ages 7 and 14 allocated to both comparison and intervention villages were measured at baseline. Additionally, household surveys were conducted in randomly selected households within the villages.

Three main selections were done to compose the subsample to be used in this study. First, since the main interest of this study was to identify family and individual risk constellations, only children with corresponding household survey data were considered (5810 children, in 2709 households, and 280 villages). Second, given that at least two risk factors contemplated in the subgroup analysis were related to the parental role (i.e., parental education and parental perception of child's ability), it was decided to exclude from the database those children who had a household survey reported by another member of the family that were not the head or the spouse of the head. This yielded a total of 4929 children. Third, given that the focus of the study is to explore the differential effects of the only intervention found to—on average—increase educational attainment, the final analyses were conducted only on a subsample of children participating in intervention 3 (1160 children in 544 households and 65 villages) and control condition (1496 children in 700 households and 85 villages). Due to missing data in the outcome variable, the effective sample for this analysis was 2359 children in 150 villages, 1042 children in 65 villages in intervention 3, and 1317 children in 85 villages in control condition. Data from participants in interventions 1 and 2 (in total 2708 in 1266 households and 130 villages) were also used for the identification of the risk subgroups, as will be explained in the analytic plan.

The study made use of child and household data collected at baseline (March and April 2005), and reading outcomes collected one year later (March and April 2006). Although theoretically the nesting of children within households is very relevant to the study, there were constraints to the use of this as a nesting level. The main constraint was the fact that 420 households had a single child in the study, posing problems on the statistical estimations. In addition, the unit of randomization for the intervention was the village, hence it was preferred to use this level as the nesting of the data for the analyses. The average number of children per village in the study is $n = 18.88$ (minimum $n = 6$; maximum $n = 31$).

2.2. Variables and instruments

The variables will be described both at the child and the village level, as both levels will be relevant to the posterior analyses. For each variable it is mentioned what their role was in the analyses, either a baseline variable used in the risk constellations, a baseline variable used as covariate, or the endline, outcome variable.

Data stemmed from either direct child measures or a household survey. This survey was answered either by the head of the family (for 1986 children) or by the spouse of the head (for 670 children). Since there is no certain information on their role (i.e., mother or father) in the surveys, in the coming sections these two are used indistinctively to represent parental variables.

2.2.1. Reading skill (baseline/risk and endline/outcome)

Reading level was measured by a direct child test with an instrument designed by Pratham, which is also used to publish the Annual Status of Education Report (by the ASER Centre). The instrument intends to measure children's level of reading fluency in Hindi (Uttar Pradesh's language). The possible levels were five: The child cannot read at all (score 0); the child can read (decode) letters (score 1); the child can read words (score 2); the child can read a paragraph (score 3); the child can read a story (score 4).

The procedure (ASER Centre, 2018) to establish the level is the following: The child is requested to read aloud a simple paragraph. If fluency is appropriate, the child has to read a short story, which also should be read with fluency (even if slowly) to be considered at the story level. If the child does not read the first paragraph fluently (i.e., reads haltingly), the child is requested to read five words from a list. If the child can correctly read at least four words, the child is considered to be at the word level. If the child is unable to read four words, the examiner requests to recognize at least 4 out of 5 letters (letter level). If

Table 1
Reading levels at baseline and end assessment.

Baseline reading level	All interventions		Intervention 3		Comparison	
	Frequency	%	Frequency	%	Frequency	%
0 – Nothing	717	14.7	168	14.5	222	14.8
1 – Reads letters	1106	22.4	265	22.8	327	21.9
2 – Reads words-paragraphs	1168	23.7	258	22.2	347	23.2
3 – Reads story	1938	39.3	469	40.4	600	40.1
Total	4929		1160		1496	
Endline reading level	Frequency	%	Frequency	%	Frequency	%
	Frequency	%	Frequency	%	Frequency	%
0 – Nothing	441	8.9	93	8.0	147	9.8
1 – Reads letters	795	16.1	191	16.5	234	15.6
2 – Reads words-paragraphs	909	18.4	202	17.4	279	18.6
3 – Reads story	2243	45.5	556	47.9	657	43.9
Total	4388		1042		1317	

that level is not reached, the child is considered to be at a beginner level.

The authors of the original study merged the ability to read words and paragraphs into one score, as they were considered to require a similar degree of ability (between simple decoding and reading fluently). The same scoring rules are followed in this study, meaning that a score 0 is given to children who cannot read at all, a score 1 to those who can decode letters, a score 2 to those who read words or paragraphs, and a score 3 to those who can fluently read a full story.

The same test was used as an indicator of reading ability at baseline and outcome measures. Table 1 presents the percentages of children reaching each score at both measure time points, for all interventions and particularly for intervention 3 and control groups.

At the village level, an aggregated average of children reading level at entry was computed to be used as context variable in the final modeling stage ($M = 1.88$, $SD = .34$; $\min = 0.82$, $\max = 2.67$).

2.2.2. Gender (Baseline/risk)

Data on child gender were collected in the household survey. Across all interventions, girls make up for 51.8% of the sample ($n = 2554$). Girls corresponded to 48.4% of intervention 3 participants and 47.8% of the comparison group. The percentages of girls in villages range from 11.8% to 75%. A dummy variable (1 = girl) was used in the construction of the constellations of risk, and a village level proportion of girls was used as a context variable in the final modeling stage.

2.2.3. Parental education (Baseline/risk)

Data on parental education were collected in the household survey. The respondent of the household survey (either head or spouse of the head of household) was asked to read a paragraph in order to determine whether he/she was literate. In the complete sample, 2815 children (57.1%) have an illiterate parent. The proportion of children with an illiterate parent was 59.1% in the intervention group, and 57.4% in the comparison group. At the village level, the percentage of children with an illiterate parent ranged from 0% to 94.7%. A dummy variable was used for the constellations of risk (illiterate parent = 1).

2.2.4. School absenteeism (Baseline/risk)

Data were collected in the household survey. The respondent was requested to indicate for each child between 7 and 14 in the sample how many days he or she had been absent from school in the last 14 days. The average number of absent days across all interventions was 6.03 days ($SD = 3.42$); in the intervention group the average was 6.26 days ($SD = 3.32$) and in the comparison group 5.95 days ($SD = 3.43$). At the village level, a variable with the average days of absence was also computed ($M = 5.98$, $SD = 1.44$, $\min = 2.43$, $\max = 10.89$ days).

2.2.5. Family size (Baseline/risk)

As part of the household survey, respondents were asked to mention all the children between ages 7 and 14 in the household, which means that children aged 0–6 and those older than 14 were not counted. Although the estimation is conservative, this variable is considered a proxy of family size. At the household level the average number of children between ages 7 and 14 across all interventions was 2.40 children ($SD = 1.38$), with a minimum of 1 and a maximum of 10. The average size of intervention households was 2.42 children ($SD = 1.49$) and that of comparison classrooms was 2.44 ($SD = 1.39$). At the village level the same mean was identified ($SD = .74$).

2.2.6. Parental information about child's educational attainment (Baseline/risk)

This variable was constructed with two main sources of information, the child's reading test previously described and the parental perception of the child's ability. The latter was an assessment conducted as part of the household survey, in which parents were asked to estimate the level of reading skill of each child in the household using the same reading levels distinguished by the test. Since both the test and the parental estimate of the child's skill are in the exact same scale, a difference score was computed to reflect how distant were the estimates done by parents as compared to the direct child assessment. Difference-scores higher than 2 (either over- or under-estimations) were considered a sign of misinformation of the parent regarding the student's educational attainment, and, therefore, a risk factor. The rationale is that parents who closely monitor the child's activity should better estimate their skill level¹. In practice most (98%) of the difference scores representing misinformation corresponded to overestimations of the child's ability in relation to the test scores. Moreover, when parents declared not to know what the skill level of the child was, were also considered an indicator of misinformation. The percentage of children whose parents could be considered misinformed about their educational attainment is 21.2% across all interventions, 21% in the intervention condition and 22.3% in the comparison group. At the village level, the proportions of children whose parents could be considered misinformed about their educational attainment ranges from 0% to 50% ($M = 20.3\%$, $SD = 11.46$). A dichotomous individual indicator of misinformation (misinformed = 1) was computed to signal this risk, together with a village-level variable with the proportion.

2.2.7. Age (Baseline/covariate)

Since there was a wide age range due to the target population of the intervention (ages 7–14), the age of the child was used as a covariate in the impact analysis. It was also considered that age could interact with the constellations of risk to predict the outcome. The average age in the full sample was 10 years 6 months ($SD = 2$ years 4 months). Both intervention and comparison group hold practically the same age average and standard deviation.

All baseline individual and village variables were balanced across intervention and control groups (analysis available upon request), except for days of absence, which was slightly higher in intervention group, with $M_i = 6.2$; $M_c = 5.9$, $t(2793) = 2.414$, $p = .016$.

2.3. Analysis

The first analytic stage corresponded to the identification of

¹ This idea assumes that the reference value is the one obtained by the child in the direct test situation. This may not be a totally correct assumption, as the test performance might be affected by many situations and therefore might not properly reflect student's skill. However, it is expected that on average, this discrepancy is a good proxy of parental information. Moreover, this was the most direct assessment of parental information about the child's performance that could be constructed from the available data.

Table 2
Log-likelihood statistics for latent class solutions.

Model	LL	n par.	BIC	CAIC	AWE	Entropy
1level-1profile	–36058.08	10	72201.19	72211.19	72316.22	1.00
1level-2profile	–35089.20	19	70339.95	70358.95	70558.51	0.87
1level-3profile	–34473.33	28	69184.73	69212.73	69506.81	0.75
1level-4profile	–33992.73	37	68300.07	68337.07	68725.68	0.79
1level-5profile	–33884.86	46	68160.86	68206.86	68689.99	0.79
1level-6profile	–33794.21	55	68056.07	68111.07	68688.73	0.80
2levels-4profile	–33689.06	40	67718.23	67758.23	68178.35	0.80

Note. LL = Log-likelihood; n par. = number of free parameters; BIC = Bayesian Information Criterion; CAIC = Consistent Akaike's Information Criterion; AWE = Average Weight of Evidence criterion.

individual and family risk constellations. This was done by means of multilevel latent profile analysis, which allowed to characterize the sample both in terms of the students' type of risks they are exposed to and the amount of them (Lanza, Rhoades, Nix, Greenberg, & Group, 2010). Latent profile analysis helps identify underlying subgroups; the multilevel aspect of it, allows the probabilities of membership to each subgroup (profile) to vary across higher level units, in this case villages. Profiles were based on a set of risk-related variables, containing dichotomous, ordinal and continuous variables, namely, reading entry scores, being a girl, illiterate parent, number of missed school days in the last 14 days, parental misinformation of educational level, and number of children aged 7–14 in the family. Following the recommendation of Henry and Muthén (2010), we first identified the best single-level solution (models of 1–6 classes) using both statistical—Bayesian Information Criterion (BIC), Consistent Akaike's Information Criterion (CAIC), the Approximate Weight of Evidence criterion (AWE), and classification precision (entropy values, average probabilities for the most likely profile)—and substantial criteria. In a second step the best latent profile solution was modelled as a multilevel latent profile model, using a parametric approach with a common factor at the village level (Henry & Muthén, 2010). From this model, predicted membership to one of the latent classes for each individual were saved in order to conduct the next analytic stage. Multilevel latent profile analysis was performed on the full sample (interventions 1, 2, 3 and 4), with the software Mplus, version 7.31 (Muthén & Muthén, 1998).

A second stage was to test whether the membership of children to a particular profile moderated the effect of the intervention on reading outcomes. Given the ordinal nature of the outcome variable, this was investigated by means of multilevel ordinal multinomial regression analysis (cumulative logit models). The main predictors were an intervention dummy (1 = Intervention 3, 0 = Control), and a set of profile dummies to investigate the main effect of class membership. Covariates were student age at the child level, and village aggregates of the individual risk variables. In line with the second research question, interaction terms between intervention and profile membership, were modelled, allowing for the effect of the intervention to vary depending on the profile membership. In line with the third research question, interaction terms were fitted in order to explore whether the association

of the students' risk profile with the outcome depended on student and village characteristics. A parsimonious approach to modeling was taken in the analyses, as suggested by Snijders and Bosker (2012). Analyses were performed with the subsample of intervention 3 and 4 (control), with the software Mlwin (Version 2.35; Rasbash, Browne, Healy, Cameron, & Charlton, 2015). To reduce the risk of biased estimates, the final model was estimated by means of Markov chain Monte Carlo methods (Browne, 2009), as suggested by Snijders and Bosker (2012).

Missing data was not a matter of great concern in the analyses, as the original study had exceptional levels of participation. The analysis conducted on the first stage (i.e., multilevel latent profile analysis) used full information maximum likelihood estimation, which means that the full sample of 4929 children was classified into a risk profile. In the second stage, there were 297 cases with missing data in the outcome variable, which needed to be excluded from the analysis because multilevel cumulative logit models require full data in order to be estimated. This represented a loss of only 1.02% of the information, yielding an effective sample of 2359 children within 180 villages.

In line with concerns about the pitfalls of null hypothesis statistical testing (NHST)—see for example, Gorard and White (2017)—the reliance on *p*-values was kept to a minimum, particularly in the final modeling stage. For that reason, results of the final multilevel model are based on Bayesian estimations, with associated credible intervals. For other multilevel models, standard *p*-value ranges are provided, in order to support modeling decisions for level 2 covariates, and for the sake of readability of a wider audience. The results of the final model are also translated into odds ratios, in order to describe differences and associations in a more practical manner.

3. Results

3.1. Stage 1: constellations of individual and family risk

Table 2 shows log-likelihood estimates for all latent profile solutions (1–6 latent profiles), while Table 3 displays profile size in each solution and the average probabilities for the most likely profile. Information criteria of 1-level models favor the largest model, that is, the 6-profile solution, as all indices (i.e., BIC, CAIC, AWE) continue to decrease with

Table 3
Profile sizes and average classification probabilities.

Model	Profile sizes						Average probability most likely profile					
	P1	P2	P3	P4	P5	P6	P1	P2	P3	P4	P5	P6
1level-1profile	1						1					
1level-2profile	.85	.15					.97	.96				
1level-3profile	.32	.53	.15				.86	.89	.94			
1level-4profile	.51	.31	.14	.04			.88	.85	.95	.96		
1level-5profile	.30	.51	.04	.05	.10		.84	.88	.96	.91	.87	
1level-6profile	.51	.05	.10	.05	.29	.01	.87	.87	.88	.91	.84	.96
2levels-4profile	.49	.33	.04	.14			.90	.86	.98	.94		

Note. P1 = Profile 1.

Fig. 1. Profile plot for 2-level 4-profile solution in mean probabilities.

the inclusion of extra classes. The decrease, however, is minimal after 4 profiles, and the addition of more clusters only seems to further separate profiles into very small subgroups, complicating interpretability. The 4-profile solution was thus used for the multilevel profiling. Profile means varied slightly but significantly across villages, with a village level variance of 0.15 ($SE = .075, p < .05$). Adding the second level to the 4-profile solution improves the model fit compared to all the other solutions tested, including the less parsimonious 6-class solution.

Fig. 1 represents the final profile solution. Data-points for dichotomous variables (girl, illiterate parent, parental misinformation) indicate the class-specific mean probabilities of having the corresponding risk factor. To simplify the depiction, the ordered categorical variable representing initial reading level was dichotomized, and it therefore displays the probability of each profile of having very low initial reading level (i.e., unable to read or reads only letters). The continuous variables representing school absenteeism (absent school days) and family size (number of children aged 7-to-14), have been rescaled into 0–1 means in order to facilitate their depiction. A description of the risk constellations represented by the identified classes will be presented next.

- **Profile 1: Low risk (48.9%).** Overall, children in this profile had a probability below average of presenting all the risk factors, except to family size, which was average. The most salient feature however was the almost null probabilities of having a low entry reading level, and of parental misinformation of the child's reading ability. The mean age of this profile was 10 years and 11 months approximately.
- **Profile 2: High academic and family risk (33.9%).** This group had a very high probability of having a low reading level at the start of the intervention. This was combined with a higher than average probability of being a girl, having an illiterate parent, and of parent misinformation of the child's reading ability (therefore, overestimating her ability). This profile has the lowest child's age mean (9 years 6 months approximately).
- **Profile 3: Average/low risk from large family (3.8%).** Children in this group have a much higher than average family size (almost 6.8 children aged 7-to-14 per family, compared to the sample average of 2.4 children). In addition, the likelihood that these children had an illiterate parent was close to the lowest level across profiles. This profile had a mean age of 10 years and 2 months approximately, slightly younger than the sample average of 10 years 4 months.
- **Profile 4: High absenteeism (14.3%).** This group had very high absenteeism rates, with 12.6 absent days in the past 14 school days (compared to the overall mean of 6 absent days). They also have the second largest probability of having an illiterate parent. In spite of that, these children have the second lowest probability of a low reading level at entry. The mean age of this profile was 11 years and

4 months approximately, the oldest profile identified.

3.2. Stage 2: prediction of reading scores after intervention

Random intercept cumulative logit models were fitted in order to test the association of class membership with reading level at the end of the intervention year. An unconditional model revealed that 6.74% of the residual variance in reading scores after the intervention was attributed to the village level. Table 4 shows the main models tested, and the final model, estimated with MCMC. Since these correspond to cumulative logit models with the highest value as reference category, negative coefficients represent a reduction in the probabilities of scoring lower than the highest score, in colloquial words, a *positive* association with the outcome.

Model 1 shows the main effects of the main predictors, intervention and profile membership, controlling for child's age—included at this stage due to its strong link to the outcomes and risk-profile membership. When other village level characteristics are not controlled for in the model, there is no evidence of impact of the full intervention 3 on student reading level at post-test. Children in profiles 2 (Academic and family risk), 3 (Low/average risk large family), and 4 (High absenteeism) are significantly more likely to obtain a lower score in the reading test post-intervention than children in profile 1 (Low risk). Finally, an increase in one year in the child's age represented a significant reduction in the probabilities of obtaining a low reading score in the post-test.

Model 2 includes village characteristics, and shows that initial reading level at the village holds a significant association with the outcome. In practice, an increase of the village reading level is associated with a significant reduction of the probabilities of obtaining low reading scores on the post-test. Also village aggregates of parental misinformation and absenteeism have small associations with the outcome. An increase in parental misinformation is associated with a small decrease in the likelihood of low reading scores, whereas an increase in village absenteeism is related to an increase in the probabilities of low reading scores. When village characteristics are controlled for, the intervention appears to have a positive impact on child reading scores.

Model 3 keeps significant village covariates from model 2, and shows two-way interaction effects between profiles and the intervention and relevant covariates.² Several of these interaction effects are stepping stones towards the three-way interaction effect between profile, intervention and village reading level explored in the last model.

² An intermediate model testing all the two-way interactions between profile memberships and significant child and village level covariates is available upon request.

Table 4
Multilevel ordered logit models for predicting reading scores.

Fixed Part	Model 1			Model 2			Model 3			Model 4			Credible interval 2.5% 97.5%
	Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.		
Threshold Reading score 0	−4.358	0.134	***	−4.259	0.126	***	−4.299	0.136	***	−4.291	0.140	−4.65	−4.01
Threshold Reading score 1	−2.576	0.112	***	−2.493	0.101	***	−2.505	0.114	***	−2.498	0.113	−2.73	−2.28
Threshold Reading score 2	−1.062	0.096	***	−0.987	0.085	***	−0.947	0.097	***	−0.944	0.096	−1.14	−0.76
Intervention 3	−0.172	0.119		−0.222	0.098	*	−0.373	0.154	*	−0.412	0.157	−0.71	−0.12
Profile 2: Academic + family risk	3.019	0.113	***	2.868	0.112	***	2.999	0.144	***	3.025	0.149	2.74	3.32
Profile 3: Large family	1.817	0.237	***	1.585	0.239	***	0.998	0.431	*	0.687	0.515	−0.32	1.66
Profile 4: High absenteeism	0.848	0.138	***	0.816	0.139	***	0.906	0.197	***	0.884	0.197	0.49	1.27
Child age T1	−0.233	0.021	***	−0.233	0.021	***	−0.264	0.035	***	−0.264	0.035	−1.94	−0.78
Village mean reading				−1.527	0.180	***	−1.035	0.263	***	−1.351	0.290	−0.33	−0.20
Village mean age				0.182	0.113								
Village girl prop.				−0.003	0.004								
Village illiterate parent prop.				−0.003	0.003								
Village misinfo. parent prop.				−0.011	0.005	*	−0.014	0.005	**	−0.014	0.005	−0.2	−0.004
Village absent days mean				0.075	0.038	*	0.078	0.040	*	0.079	0.040	0	0.16
Village N children 7–14 mean				−0.019	0.077								
Intervention X Prof. 2							0.324	0.201		0.281	0.205	−0.11	0.68
Intervention X Prof. 3							−0.440	0.494		0.048	0.683	−1.28	1.32
Intervention X Prof. 4							0.205	0.288		0.240	0.286	−0.30	0.80
Int. X V.mean reading							−0.013	0.313		0.857	0.444	0.02	1.74
Prof. 2 X V.mean read							−0.258	0.298		0.319	0.382	−0.42	1.08
Prof. 3 X V.mean read							−2.904	0.829	***	−3.704	1.318	−6.36	−1.16
Prof. 4 X V.mean read							−1.002	0.478	*	−0.447	0.691	−1.81	0.88
Prof. 2 X child age							0.192	0.046	***	0.190	0.047	0.10	0.28
Prof. 3 X child age							−0.303	0.106	**	−0.312	0.111	−0.53	−0.09
Prof. 4 X child age							−0.237	0.067	*	−0.244	0.069	−0.37	−0.11
Int. X Prof. 2 X V.mean read										−1.576	0.608	−2.78	−0.40
Int. X Prof. 3 X V.mean read										0.888	1.709	−2.51	4.17
Int. X Prof. 4 X V.mean read										−1.372	0.948	−3.24	0.56
Random Part													
Between village variance ($\sigma^2_{\alpha_k}$)	0.233	0.059		0.054	0.038		0.08	0.042		0.085	0.051		

Note: *** $p < .001$; ** $p < .01$; * $p < .05$.

Table 5
Predicted probabilities of reading scores and odds-ratios of reading levels per profile, based on estimated coefficients (Model 4).

Profile	Probability of reading levels				Odds ratios for reading fluently (OR p_x vs p_1)
	Nothing	Letters	Words/ Paragraph	Story	
P1: Low risk	.01	.06	.20	.72	-
P2: High academic/family risk	.22	.41	.26	.11	0.05
P3: Average risk large family	.03	.12	.29	.56	0.50
P4: High absenteeism	.03	.14	.32	.51	0.41

Note. Reference category was profile 1 (Low-risk); Odds-ratios on the table correspond to the reciprocal of those reported in the text.

This model suggests that the positive impact of the intervention on reading performance is not moderated by profile membership. The association of village reading level with the outcome, on the other hand, is moderated by profile membership, and the same applies for the relation of child age and the outcome. This model also indicates that the interaction effect among intervention and village reading level practically inexistent.

Final model 4 includes previous main effects and two-way interactions, and adds a three-way interaction between profile, intervention and village reading level. The coefficients corresponding to this model are derived from MCMC estimation, and therefore they have a corresponding Bayesian credible interval. In order to facilitate interpretation of the final model, the log-odds have been transformed into the probabilities of scoring at the highest level of the outcome (i.e., reading fluently) given the most relevant combinations of the main predictors, with the other categorical predictors in zero (i.e., reference categories) and continuous predictors centered at the grand mean (Tables 5–7). Table 5 shows the adjusted predicted probabilities associated with the four different risk profiles. Children in profile 1 (Low risk) are

significantly more likely than children in profile 2 (High academic and family risk) and 4 (High absenteeism) to obtain higher reading scores. In an odds ratio scale, children in profile 1 are more than twenty times more likely than children in profile 2 to be able to read fluently at post-test (OR = 20.40). Compared to children in profiles 3 and 4, children with lower risk are more than twice as likely to be able to read fluently (OR_{p1 vs p3} = 2.01; OR_{p1 vs p4} = 2.43). Moreover, main effects confirm that the intervention reduces the probabilities of scoring low at post-test. Also increases in child's age and village reading levels are significantly associated with higher reading scores at post-test.

Table 6 shows the probabilities associated to two-way interaction effects explored in this final model. The coefficients confirm that the effect of the intervention is not moderated by risk constellations, which is expressed in probabilities in Section 6.1. Probabilities show that for all risk profiles, there was an increased chance to perform better in intervention villages. Village reading level, on the other hand, did make a difference in the likelihood of profiles to read fluently at post-test, indicating that some profiles are more sensitive to the village reading level than others. The largest difference is between profiles 1 (Low risk)

Table 6
Predicted probabilities based on estimated two-way interaction effects (Model 4).

		Nothing	Letters	Words/ Paragraph	Story
<i>Section 6.1</i>					
Profile 1	Intervention	.01	.04	.15	.79
	Control	.01	.06	.20	.72
Profile 2	Intervention	.20	.40	.28	.13
	Control	.22	.41	.26	.11
Profile 3	Intervention	.02	.09	.25	.64
	Control	.03	.12	.29	.56
Profile 4	Intervention	.03	.12	.30	.56
	Control	.03	.14	.32	.51
<i>Section 6.2</i>					
Profile 1	V.read (M - 1SD)	.02	.09	.27	.62
	V.read (M + 1SD)	.01	.04	.15	.80
Profile 2	V.read (M - 1SD)	.29	.42	.21	.08
	V.read (M + 1SD)	.17	.38	.30	.15
Profile 3	V.read (M - 1SD)	.14	.34	.33	.20
	V.read (M + 1SD)	.01	.03	.11	.85
Profile 4	V.read (M - 1SD)	.06	.21	.36	.37
	V.read (M + 1SD)	.02	.08	.24	.66
<i>Section 6.3</i>					
Intervention	V.read (M - 1SD)	.01	.05	.17	.76
	V.read (M + 1SD)	.01	.04	.14	.82
Control	V.read (M - 1SD)	.02	.09	.27	.62
	V.read (M + 1SD)	.01	.04	.15	.80
<i>Section 6.4</i>					
Profile 1	Age (M - 1SD)	.02	.11	.28	.58
	Age (M + 1SD)	.01	.04	.13	.82
Profile 2	Age (M - 1SD)	.25	.42	.24	.10
	Age (M + 1SD)	.19	.39	.28	.13
Profile 3	Age (M - 1SD)	.10	.28	.35	.27
	Age (M + 1SD)	.01	.04	.14	.81
Profile 4	Age (M - 1SD)	.10	.29	.36	.25
	Age (M + 1SD)	.01	.05	.17	.77

Note. Reference category was profile 1 (Low-risk).

Table 7
Predicted probabilities based on estimated three-way interaction effect (Model 4).

			Nothing	Letters	Words/ Paragraph	Story
Profile 1	Intervention	V-read (M - 1SD)	.01	.05	.17	.76
		V-read (M + 1SD)	.01	.04	.14	.82
	Control	V-read (M - 1SD)	.02	.09	.27	.62
		V-read (M + 1SD)	.01	.04	.15	.80
Profile 2	Intervention	V-read (M - 1SD)	.31	.42	.20	.07
		V-read (M + 1SD)	.12	.33	.34	.21
	Control	V-read (M - 1SD)	.29	.42	.21	.08
		V-read (M + 1SD)	.17	.38	.30	.15
Profile 3	Intervention	V-read (M - 1SD)	.06	.21	.35	.38
		V-read (M + 1SD)	.01	.04	.13	.82
	Control	V-read (M - 1SD)	.14	.34	.33	.20
		V-read (M + 1SD)	.01	.03	.11	.85
Profile 4	Intervention	V-read (M - 1SD)	.06	.21	.36	.37
		V-read (M + 1SD)	.01	.06	.20	.73
	Control	V-read (M - 1SD)	.06	.21	.36	.37
		V-read (M + 1SD)	.02	.08	.24	.66

Note. Probabilities in boldface correspond to significant coefficients in Model 4. Reference category was profile 1 (Low-risk).

and 3 (Average/low-risk, large family), as seen in Table 6, Section 6.2. Both the Low-risk group and the Average/low-risk from large family group are similarly likely to read fluently at post-test when they belong to a village with a reading level one standard deviation above the mean. However, when they are embedded in a village with a low average reading level (i.e., one standard deviation below the mean), the Low-risk group is much more likely to obtain the highest reading score than the Average/low risk group (OR = 6.7). Table 4 also reveals that the

intervention impact differs depending on village reading level. Table 6, Section 6.3 helps understand this interaction effect: Children³ in intervention villages are almost equally likely to read fluently at post-test, regardless of the reading level of the village. However, given a low reading level at the village, children in the intervention condition are almost twice as likely to reach the highest score at post-test than children in the comparison group (OR = 1.94). In other words, the intervention seems to compensate for contextual differences for children with low-risk. The last two-way interaction listed in Table 4 is between child risk-profile and age. Table 6, Section 6.4 shows that the overall protective influence of age found for the Low-risk group is stronger for profiles 3 (Average/low risk, large family) and 4 (High absenteeism). While older children (one standard deviation above mean) score fairly similarly across these three groups, younger children from these profiles perform significantly worse than Low-risk children of the same age (OR_{p3 vs p1} = 0.24; OR_{p4 vs p1} = 0.23). For profile 2 (Academic/family-risk), however, this protective function of age is inexistent, and they tend to perform similarly poorly regardless of their age.

Finally, model 4 reveals that there is a three-way interaction between intervention, risk profile and village literacy level, which is expressed in probabilities in Table 7. This suggests that the intervention's compensatory effect for contextual differences (i.e., village literacy level) does not hold for children in all risk profiles. Children in the Low risk and in the Average/low risk from large family profile do benefit from the compensatory effect of the intervention. However, children in the Academic/family-risk and in the High absenteeism profiles appeared to be much more sensitive to the contextual reading-level, and this influence is not compensated by the intervention. Put differently, if the village reading level is low, children in the Academic/family-risk and High absenteeism groups will perform just as poorly in control and intervention villages, whereas children in the Low and Low/Average-risk profiles will have significantly better chances to get the highest reading score if they are in intervention villages.

4. Discussion

The present study intended to explore possible variations in the impact of the Pratham Information Project (Banerjee et al., 2010), implemented in the rural district of Jaunpur, state of Uttar Pradesh, India. The goal was to explore whether the positive impact of the most comprehensive intervention differed depending on diverse constellations of individual and family risk held by the participant children. Moreover it was explored how the diverse risk profiles interacted with other characteristics of children and the context in order to produce the outcomes.

Four constellations of risk were identified, all of which had distinctive features. The High academic- and family-risk profile concentrated the poorest readers, relatively more likely to be girls, with an illiterate parent who more often overestimated their reading level. The High absenteeism profile concentrated children with a higher than average reading level, but who miss school often. The Average/low-risk from large family grouped children with a lower than average probability of having an illiterate parent and the largest family size. Finally, the Low-risk profile concentrated relative advantages in all risk factors, particularly a good reading level at entry, relatively low likelihood of an illiterate parent and a null chance of parent misinformation about the child's reading performance. The risk profiles performed consistently differently on the outcome: Children in the High academic- and family-risk profile and in the High absenteeism profile were much less likely than children in the Low-risk profile to read fluently at the post-test. These differences also depended on child's age, with age

³ The reader is reminded of the fact that these are adjusted probabilities, therefore these correspond to children from profile 1 (low risk), with average values in individual and village controls.

performing as a protective factor for almost all profiles, with the exception of children with High academic and family risk. Other studies have identified profiles of risk factors in the context of educational interventions (e.g., Cooper & Lanza, 2014), also highlighting the idea that factors do not necessarily relate linearly to each other, but can coexist generating distinctive combinations and types of risk. The identification of one subgroup that concentrates multiple sources of risk, and another one that accumulates relative advantages in all risk domains, is in line with other studies in Anglo-American (e.g., Cooper & Lanza, 2014) and European (e.g., Mascareño, Doolaard, & Bosker, 2013) samples. Such person-oriented approach better describes the heterogeneity and complexity of risk in the context of rural India.

Importantly, our analysis confirmed that the intervention implemented by Pratham had a significant positive impact on children's reading level after controlling for child and village characteristics and several interactions among such factors. Although not the focus of our explorations, this is not a surprising result, as the core of this intervention was the intensification of concrete opportunities for learning to read in the intervention villages. This is the mechanism that is known to be the most effective in improving children's learning outcomes in developing countries (e.g., Snilstveit et al., 2015). In line with our main inquiries, it was explored whether this positive effect of the intervention was moderated by profile membership, and our analysis revealed that such differential effects are not present in the data. In other words, the intervention could be considered beneficial for all children.

A more complete set of interaction terms, however, provided a more nuanced view on the effects of the intervention given characteristics of the context and children. The findings indicated that in the context of low to average individual risk, the intervention was able to buffer contextual risk and compensated for low skill capital at the village level. In other words, for students with low-risk the intervention was equally effective in villages with low- and high-reading level, whereas low-risk children in control villages with low reading levels underperformed similar children in villages with higher reading levels. This compensatory effect, however was not observed for children with academic and family risk and with high absenteeism. For these children the intervention was more effective when they were embedded in villages with higher average reading scores. Under those conditions, children with academic risk in intervention villages were able to outperform similar children in equivalent contexts in the control condition. Village reading level was also found to significantly interact with the risk profiles: Whereas all profiles benefited from higher contextual reading levels, children in the average/low-risk from large families profile seem to be particularly sensitive to such contexts. This meant that when part of villages with low reading levels, these children performed much worse than low-risk children, but when embedded in a more advantageous context they performed equally well as low-risk children. Above and beyond these interaction effects, village-level reading scores uniquely contributed to predict children's reading scores.

The crucial role of community skill capital—i.e., village reading level—on the effect of an educational intervention is a finding in line with theoretical assumptions as well as with empirical evidence. The findings come to emphasize the theoretical idea that contextual characteristics can have a unique role in reinforcing or buffering risk factors observed at the family and individual level (Feinstein et al., 2004). Community skill capital can lead to strengthening or weakening the expected effects of an intervention, and therefore should be anticipated and actively considered in the development of a program theory. Since the intervention developed by Pratham recruited volunteer villagers to provide the reading camps to children, the community literacy level might have directly affected the quality of reading instruction received by children. Indeed, meta-analytic evidence from educational interventions in developing countries indicate that there might be a

minimum community capital level for an intervention to work properly, which is particularly true for interventions that largely rely on the community's involvement such as the Pratham Information Project (e.g., Snilstveit et al., 2016). It has even been shown that when interventions are complex, potentially negative effects can be observed if communities do not possess a minimum social capital in order to support that educational intervention (Blimpo, Evans, & Lahire, 2013).

The results reported in this study provide guidelines to more accurately focus intervention efforts in developing countries. Educational interventions are called to at least partially compensate for the effects of risk associated with lack of developmental and learning opportunities of children with stronger disadvantage. One possible way to achieve this compensatory impact is to design levels of intervention according to risk profiles, taking into account the interaction among individual but also family and community factors. Moreover, it seems important to highlight that if risk is considered to be systemic and multilevel, interventions should also respond to that logic. In that sense, it is somewhat discouraging that the only condition within the Pratham intervention project that had an impact on student outcomes is the one where the school system was completely skipped (Banerjee et al., 2010). While the intervention provided children with concrete reading learning opportunities by engaging villagers in reading camps, the impact might have been strengthened if also schools had been involved in the intervention. An approach that engages both the community and the school in improving daily learning opportunities for children might be a more sustainable way to also deal with differences in social capital across villages.

There are several limitations to this study. As any secondary analysis, the explorations here were constrained by the characteristics of the already collected data. In this case an interesting addition would have been to take school characteristics into account, and also explore potential differential effects in that line. However, since this intervention did not work with schools as units of intervention but on villages, the structure of the original datasets did not provide the possibility to associate children to a school. Other limitations have to do with the type of analysis implemented. Since latent profile analysis uses a probabilistic model to define profile membership, there is always a degree of uncertainty in profile membership that could attenuate the relationships with other variables, for example, a distal outcome. Adjustment methods have been developed to address this issue (see Bak & Vermunt, 2016 for a comparison of methods) but due to technical issues with the dataset and software, these were not fully implemented. Instead, the classification to latent profiles was done first and then modal assignment was used to predict the distal outcome. Given the known problems with this strategy, it is likely that the relations between profile membership and outcomes are stronger than those reported.

Declarations of interest

None.

Author's note

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