Received: 14 April 2020 | Revised: 15 October 2020 | Accepted: 5 January 2021

DOI: 10.1002/hec.4224

RESEARCH ARTICLE

Health Economics WILEY

Child labor and psychosocial wellbeing: Findings from India

Simon Feeny[1] | **Alberto Posso**[1] | **Ahmed Skali**[2] | **Amalendu Jyotishi**[3] | **Shyam Nath**[4] | **P. K. Viswanathan**[5]

[1]Centre for International Development, School of Economics, Finance and Marketing, RMIT University, Melbourne, Australia

[2]Faculty of Economics and Business, University of Groningen, Groningen, The Netherlands

[3]School of Development, Azim Premji University, Bangalore Urban, Karnataka, India

[4]Center for Economics and Governance, Amrita University, Amritapuri, Kerala, India

[5]Department of Management, Kochi, Kerala, India

Correspondence
Alberto Posso, RMIT University, Melbourne, Victoria, Australia.
Email: alberto.posso@rmit.edu.au

Abstract

Mental health is a neglected health issue in developing countries. We test if mental health issues are particularly likely to occur among some of the most vulnerable children in developing countries: those that work. Despite falling in recent decades, child labor still engages 168 million children across the world. While the negative impacts of child labor on physical health are well documented, the effect of child labor on a child's psychosocial wellbeing has been neglected. We investigate this issue with a new dataset of 947 children aged 12–18 years from 750 households in 20 villages across five districts of Tamil Nadu, India. Our purpose-built survey allows for a holistic approach to the analysis of child wellbeing by accounting for levels of happiness, hope, emotional wellbeing, self-efficacy, fear and stress. We use a variety of econometric approaches, some of which utilize household-level fixed effects and account for differences between working and nonworking siblings. We document a robust, large and negative association between child labor and most measures of psychosocial wellbeing. The results are robust to a battery of exercises, including tests for selection on unobservables, randomization inference, instrumental variable techniques, and falsification exercises.

KEYWORDS
child labor, child wellbeing, India, mental health

JEL CLASSIFICATION
I31, J13, J22

1 | INTRODUCTION

Child labor is defined as work that deprives children of their childhood, potential and dignity, and that is harmful to their physical and mental development International Labor Organization (ILO, 2019a). Despite falling recently, the latest estimates indicate that globally, 168 million children aged 5–17 are engaged in child labor (UNICEF, 2019a). India is home to approximately 6% of the world's child laborers. Its 2011 census found that 10.1 million children between the aged 5–14 worked. Over 80% of India's child laborers were in rural areas, and girls comprised 45% of the total (UNICEF, 2019b).

Some children's work is neither harmful nor exploitative and is unlikely to affect their health and education. However, many others are involved in work that deprives them of education and places them in hazardous conditions. The worst forms of child labor include forced and bonded labor, child soldiering, sexual exploitation, or involvement in other illicit activities (ILO, 2019a). In India, children are often employed in manual labor such as cotton growing, the matchbox industry, lock-making factories, mining and quarrying, and tea plantations. In rural areas, most child workers are cultivators or agricultural workers (UNICEF, 2019b).

Child labor is likely both a symptom and a cause of poverty, with potentially devastating impacts that often last into adulthood. These impacts include lower levels of education through poorer school attendance and attainment (ILO, 2015) and worse physical health, sometimes through exposure to physical harm and injury (Ahmed & Ray, 2014; Hughes et al., 2017; Parker, 1997).

This paper examines a largely neglected potential consequence of child labor: its impact on psychosocial wellbeing. While such impacts are recognized in theory, there is little empirical literature on the effects of labor on various dimensions of psychological wellbeing. This is an important question given that childhood health has long-lasting consequences for adult mental health (Llena-Nozal, Lindeboom, & Portrait, 2004). Conceptually, the World Health Organization (WHO) highlights the following mechanisms by which work affects children's psychological health: (i) the underuse of skills, (ii) excess work or lack of control over work conditions, (iii) low/no payment, (iv) lack of time for recreation/rest, (v) lack of time with family; (vi) difficulties combining work and school, (vii) physical punishments, intimidation or isolation, and/or (viii) conflictive roles in the family or community (WHO, 1987).

We document a robust negative association between child labor and psychosocial wellbeing. We argue that this association is likely causal. Only a handful of studies have examined the relationship between child labor and mental health, with contrasting approaches and results.[1] We review these studies in Section 2 but highlight our contributions here.

First, the literature has not examined a comprehensive range of psychosocial measures which child labor is likely to influence. Second, it mostly focuses on children living in urban locations, ignoring the large proportion of rural child workers. Most child workers worldwide live in rural areas, engaged in the often-precarious agricultural sector (ILO, 2019b). Third, previous studies typically report correlations that are only conditional on small sets of controls. Fourth, they do not explicitly address causality.

This paper aims to fill these gaps and contribute to the literature in four ways. First, we examine the impact of child labor on a broad set of psychosocial measures. These include happiness, hope, emotional wellbeing, self-efficacy, and measures of being scared and being stressed. These variables are validated dimensions of child wellbeing that are likely to be affected by work (Helliwell, Layard, & Sachs, 2018; Keyes et al., 2012; Schwarzer & Jerusalem, 1995; Snyder et al., 1997).

Second, we collected data in Tamil Nadu, a predominantly agricultural State of India. Data were collected using a unique survey specifically designed to capture measures of children's psychosocial wellbeing. Tamil Nadu has a high prevalence of child labor, with an estimated 284,000 children either working full time or after school (UNICEF, 2016). Details are provided below. Third, we estimate the relationship between wellbeing and child labor using a variety of econometric techniques to account for important sources of omitted variable bias using an array of controls, with some specifications using household fixed effects. Fourth, we estimate econometric models that are consistent with a causal interpretation of the results.

In some specifications, we compare siblings within households in which at least one of the siblings works and at least one does not—we refer to this as *within* household estimates.[2] Our within-household results can be interpreted as causal under the assumption that, in families with working and nonworking siblings, child labor is quasi-randomly assigned, conditional on gender and the number of younger and older siblings of each gender. Thus, we exploit the idiosyncratic component of the variation in work status that is not due to the child's gender and birth order or to gender-specific birth-order effects. We thus compare observationally identical children and test how differences in work status potentially affect measures of psychological wellbeing. This idiosyncratic variation is plausibly random, thus offering a reasonably strong basis for identification.

We recognize, however, that parents likely select which of their children work based on unobserved characteristics, such as ability, and not simply based on gender-specific birth order. Using the method proposed by Oster (2019), we examine how large selection on unobservable characteristics would have to be to make the coefficient of child labor indistinguishable from zero in our regressions. We find that to explain away our results, selection on unobservables would have to be implausibly large. While we cannot entirely rule out this problem, we interpret our results as unlikely to be driven by selection bias. Nevertheless, we err on the side of caution and apply additional econometric methods to infer causality. These include randomization inference tests and internal instrumental variables that exploit orthogonality conditions in the data. Finally, we test the validity of our results in a falsification exercise that replaces child labor with a measure that indicates if the child performs household chores. The results suggest that it is likely work, not chores, that significantly affects psychological wellbeing.

In Section 2, we review the existing literature on the relationship between child labor and psychosocial wellbeing. Methods are presented in Section 3. The first part of that section discusses the survey data collected and used to examine the relationship between child labor and measures of psychosocial wellbeing. The second part of the section discusses the empirical strategy. Results and their interpretation are provided in Sections 4 and 5. The results are discussed in Section 6 and the paper concludes in Section 7.

2 | RELATED LITERATURE

Existing work has studied the correlation between child labor and psychosocial wellbeing in a variety of settings, with mixed results. Aransiola and Justus (2018) used a sample of working-age individuals (aged 16 and over) from Brazil. They found that adults who started working at the ages of 10–14 were more likely to be diagnosed with depression relative to those who started working later. Their sample only focuses on individuals working at the time of the survey and those who live with their mothers. The latter was done to add controls for the mother's characteristics, but potentially introduces selection bias into their estimates.

Atalay et al. (2000) used a sample of 2400 children aged 8–15 across four major Ethiopian towns. They conducted a Diagnostic Interview for Children and Adolescents (DICA), a test that creates indices of anxiety, depression, and behavioral problems. Surprisingly, they found a lower prevalence of disorders among child laborers and argue that this is likely due to a healthy-worker selection effect. This is a type of selection bias that arises due to healthier children being the ones engaged in labor. In another study for Ethiopia, Fekadu, Alem, and Hägglöf (2006) applied the DICA to a random sample of 528 child laborers aged between 5 and 15 and 472 child nonlaborers. In contrast, they found that child laborers were more likely to have mood and anxiety disorders.

Al-Gamal, Hamdan-Mansour, Matrouk, and Nawaiseh (2013) used a Strengths and Difficulties Questionnaire (SDQ) and a Coping Efficiency Scale to assess emotional and behavioral problems among 4000 children aged 6–16 in Jordan. In their study, the enumerators collected data face-to-face with younger children (grades 1–6) while older children (grades 7–10) completed surveys independently. They found that working children attending school reported psychosocial problems more often than working children not attending school. Bandeali et al. (2008) also used the SDQ to assess psychosocial wellbeing of 225 working children aged 11–16 in three urban squatter settlements of Pakistan. To be included in the study, children had to be working outside of their homes. Children completed the survey themselves but were assisted by members of the research team if they were unable to read or write. They found that 10% of working children experienced behavioral problems. Finally, Nuwayhid, Usta, Makarem, Khudr, and El-Zein (2005) assessed mental health by comparing a sample of 78 male working children aged 10–17 to 60 nonworking male schoolchildren in Lebanon. They use validated anxiety, hopelessness and self-esteem questionnaires and found no statistically significant differences between the two groups.

We decided against using DICA and SDQ in this study. DICA is designed to cover a wide range of psychiatric disorders including attention deficit-hyperactivity disorder, depression, generalized anxiety, obsessive-compulsive disorder and eating disorders. However, it takes one to two hours to administer and Ezpeleta et al. (1997) found only a low to moderate degree of diagnostic agreement between the DICA and actual clinicians. The SDQ focuses on behavioral problems and comprises 25 survey items. However, its applicability to developing countries (including India) has been called into question (Goodman et al., 2012).

In our purpose-built survey, we study a broad variety of psychosocial outcomes, including happiness, hopefulness, emotional wellbeing, self-efficacy, fear, and stress, while ensuring that the data collection was not overly onerous for the child participants. The child hope and self-efficacy scales measures are validated measures, specifically designed for children and adolescents, while happiness, emotional wellbeing and being scared or stressed are simple questions with children asked to respond using a Likert scale.

The existing literature mostly focuses on children living in urban locations. This is the case in Nuwayhid et al. (2005), Atalay et al. (2000), Bandeali et al. (2008) and Fekadu et al. (2006). Other studies use nationally representative data, yet only Aransiola and Justus (2018) use location controls. This is an important shortcoming given that most child workers live in rural areas and are engaged in the often-precarious agricultural sector (ILO, 2019b). To address this shortcoming, we study child labor in a rural setting (Section 3.1).

Finally, the reviewed studies do not formally attempt to undertake an analysis that can infer causality, and typically condition their results on few control variables. In contrast, our results are robust to a vast battery of controls, and we explicitly address issues of causality and selection.

3 | METHODS

3.1 | Data and procedures

3.1.1 | Data collection

We collected data in Tamil Nadu, a predominantly rural and agricultural State in southern India. The data collection period was June-September 2018, which coincides with mid-to-late summer, when children are most likely to work. Thus, the sample period allows us to capture which children work, and which do not. The agricultural sector was chosen because most child labor in India occurs in agriculture.

Tamil Nadu comprises of seven agro-climatic zones, which are defined by soil characteristics, rainfall distribution, irrigation and cropping patterns, and other ecological characteristics (Directorate of Horticulture and Plantation Crops, 2019). We selected villages to reflect the diversity of agro-climatic zones, and thus, the diversity of agricultural activities pursued by farm households. Table O1 (online Appendix) summarizes the locations covered by the study.[3]

Households with adults and children were randomly selected based on the layout of the houses in the villages. Households were chosen if they had children aged 12–18 at the time of the survey. Questionnaires were administered by trained surveyors and children were surveyed in their homes. The data collection was done through a mobile application installed on the enumerators' smartphones. Enumerators were trained by the research team on how to use the application and fill in the responses. The enumerators carried a hard copy of the questionnaire and updated the data in the mobile application after the completion of the survey.

The questionnaire was prepared in English, then translated to Tamil by the Indian research team. The Tamil version was checked for reliability by subject matter and language experts. A pilot study was undertaken in one of the villages, which resulted in minor edits to the survey. The survey questions were read out to the children by the enumerators.

The survey was designed to capture information on all household members. As a result, we were sometimes able to survey multiple children from the same household. We obtained data from 947 children from 750 households in 20 villages across five districts. The location of each district and the sample size by district are provided in Figure 1.

We surveyed up to seven children per household—63% of households had one child respondent, 22% had two, 9% had three, and 6% had four or more. 41% of the children were female.

3.1.2 | Ethics

The research team followed best practice when administering the survey. Prior to undertaking the survey, enumerators visited the villages and obtained permissions from Village Administrative Officers. A university research ethics committee approved the project following a formal application and review.

3.1.3 | Child labor

To classify whether participants were involved in child labor, a question from the ILO child labor surveys was asked: *During the past week, did you do any of the following activities, even for only one hour?* The activities in Table 1 followed. Over 18% of the sample (171) were classified as working according to this definition.[4]

3.1.4 | Psychosocial measures of wellbeing

We employ measures of happiness, hope, emotional wellbeing, self-efficacy, being scared and being stressed. The variable choice is based on existing studies examining child wellbeing and hypothesized relationships between child

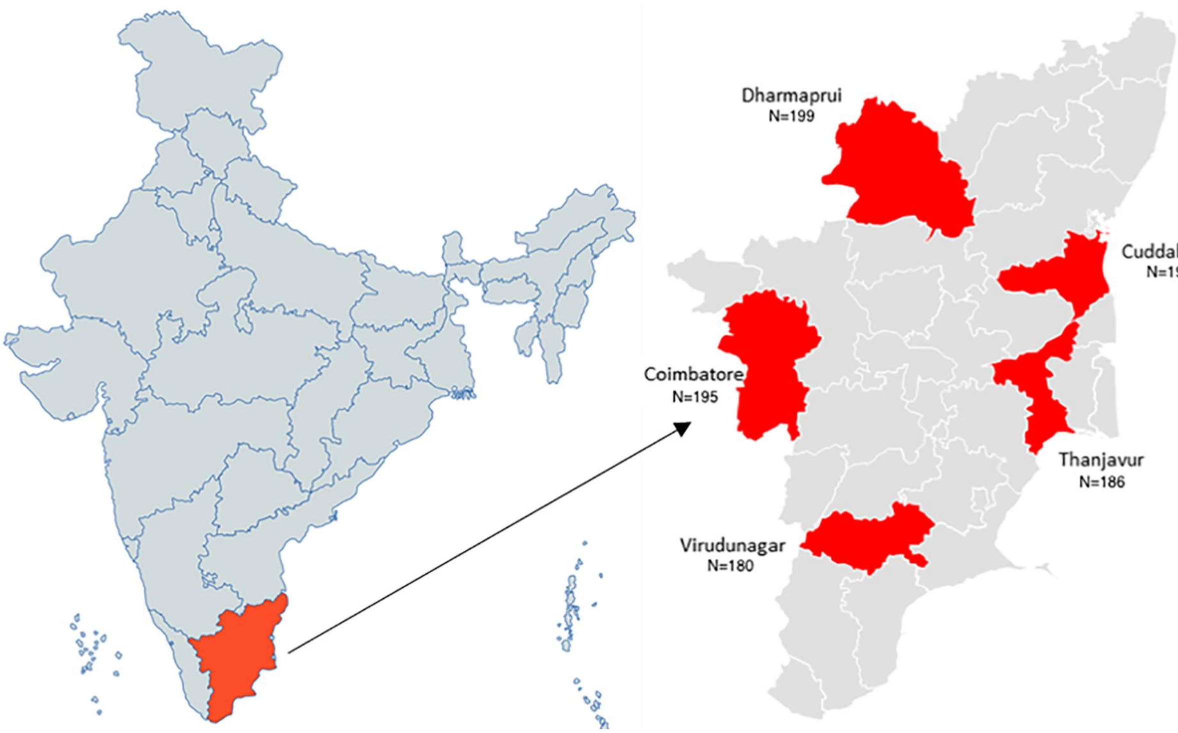

FIGURE 1 Location of Tamil Nadu and the surveyed districts

TABLE 1 Work undertaken for a wage, salary, commission or any payment in kind. A child may perform more than one type of work

Type of Work *During the past week, did you do any of the following activities, even for only one hour?*
Do any work for a wage, salary, commission or any payment in kind (excl. domestic work)? Examples: a regular job, contract, casual or piecework for pay, work in exchange for food or housing (excl. domestic work).
Do any work as a domestic worker for a wage, salary or any payment in kind?
Help unpaid in a household business of any kind? (Do not count normal housework.) Examples: Help to sell things, make things for sale or exchange, do the accounts, clean for the business, etc.
Do any work on the household's plot, farm, food garden, or help in growing farm produce or by looking after animals for the household? Examples: Plowing, harvesting, and looking after livestock.
Do any construction or major repair work on his/her own home, plot, or business or those of the household?
Catch any fish, prawns, shells, wild animals or other food for sale or household food?
Produce any other good for this household's use? Examples: Clothing, furniture, clay pots, etc.

labor and different states of psychosocial wellbeing. As previously noted, these variables are established and validated measures of child psychosocial wellbeing. Tables O2 and O3 (online Appendix) list the definitions of all variables and survey questions.

The first variable captures a child's overall level of wellbeing by asking them how often they are happy. Each child was asked, “during the past week, how often did you feel happy,” with the following responses provided on a Likert scale: (1) never, (2) once or twice, (3) about once a week, (4) two or three times a week, (5) almost every day, and (6) every day.

Hope is measured with the scale developed in Snyder et al. (1997). The scale is based on the responses to six questions that asked how often children felt they experienced different situations using a Likert scale of 1–6, in which 1 is none of the time and 6 is all the time. The statements each child was asked to classify are: (i) "I think I am doing pretty well"; (ii) "I can think of many ways to get the things in life that are most important to me"; (iii) "I am doing just as well as other children my age"; (iv) "When I have a problem, I can come up with lots of ways to solve it"; (v) "I think the things I have done in the past will help me in the future"; and (vi) "Even when others want to quit, I know that I can find ways to solve the problem".

Self-efficacy was measured using a scale from Schwarzer and Jerusalem (1995), based on the responses to 10 statements using a Likert scale ranging from 1–4. The scale asked children to score their agreement with the following statements: (i) "I can always manage to solve difficult problems if I try hard enough"; (ii) "If someone opposes me, I can find the means and ways to get what I want"; (iii) "It is easy for me to stick to my aims and accomplish my goals"; (iv) "I am confident that I could deal efficiently with unexpected events"; (v) "Thanks to my resourcefulness, I know how to handle unforeseen situations"; (vi) "I can solve most problems if I invest the necessary effort"; (vii) "I can remain calm when facing difficulties because I can rely on my coping abilities" (viii) "When I am confronted with a problem, I can usually find several solutions"; (ix) "If I am in trouble, I can usually think of a solution"; and (x) "I can usually handle whatever comes my way".

Following Keyes et al. (2012), we assess emotional wellbeing as the average response to 12 questions that asked children how often they experience various positive emotions using a Likert scale of 1–6, where 1 is none of the time and 6 is all of the time. The questions asked children to rate how often in the last 2 weeks they felt: (i) happy; (ii) bored; (iii) that they had something important to contribute to society; (iv) that they belonged to a community (like a social group, fan club, school or neighborhood); (v) that their society is becoming a better place for people like them; (vi) that people are basically good; (vii) that the way their society works made sense to them (viii) that they liked most parts of their personality; (ix) that they are good at managing the responsibilities of their daily life; (x) that they had warm and trusting relationships with other children; (xi) that they had experiences that challenged them to grow and become better persons; and (xii) that they are confident to think or express their own ideas and opinions.

Responses to the question "Over the past week, how often did you feel scared without any good reason?" measure fear. Finally, child respondents were asked to indicate how stressed they felt by indicating it on a small ruler. Both variables take values from 1–6, with higher values indicating higher levels of fear and stress.

3.1.5 | Control variables

Other survey questions were devised to collect data for control variables. Some variables were measured at the household level, derived from the survey of adult respondents.

The regression analysis controls for child characteristics, such as age, gender, number of older and younger siblings, and a dummy variable equal to 1 if the child regularly attends school. In terms of household characteristics, we included a wealth index and average household expenditure per month.

3.2 | Empirical approach

We begin by estimating variants of the following equation:

$$Wellbeing_{ihj} = \alpha_0 + \gamma_j + Child\ Work_{ihj}\beta + X_{ihj}\delta + Z_{hj}\theta + \varepsilon_{ihj} \tag{1}$$

where, wellbeing of child i in household h and village j is regressed on *Child Work*, a dummy variable equal to 1 if child i works, and 0 otherwise. Vectors X and Z are child-specific and household-level controls, respectively. We also include a vector of village dummies γ_j; a constant term α_0; and an idiosyncratic error term, ε.

Equation (1) uses all available variation within and between households. An immediate shortcoming is that we are comparing children from a wide variety of family environments that may differ in terms of both child labor and wellbeing. Thus, we next estimate:

$$Wellbeing_{ihj} = \eta_0 + \lambda_h + Child\ Work_{ihj}\psi + X_{ihj}\chi + \mu_{ihj}, \tag{2}$$

where, λ_h represents household-level fixed effects. We estimate Equation (2) for a subset of the sample where more than one child was interviewed per household—342 children from 145 households. The inclusion of household fixed effects allows us to control for unobserved characteristics that can influence psychosocial wellbeing and are common to all children within a household, including caste, religion, location, parent characteristics, and a host of environmental factors. Thus, the dependent variable in Equation (2) is de-meaned wellbeing, by household. Equation (2) effectively models child psychosocial outcomes while absorbing all common unobserved factors to the extent they affect child outcomes in a linear and additive way.[5] Since Equation (2) controls for all factors common to all children within the same household, it does not need to separately include independent household-level control variables, Z.

De-meaning wellbeing by household presents another limitation—the estimation sample for Equation (2) will include households with more than one child in which children do not vary by work status (all working or all nonworking). Thus, the coefficient of *Child Work* in Equation (2) will reflect both within and between family differences in wellbeing between working and nonworking children. We therefore also ran versions of Equation (2) which restrict the sample to only households in which at least one child works and at least one does not. Here, the coefficient of *Child Work* reflects differences in wellbeing between a sibling who works and a sibling who does not.

Interpreting such differences in wellbeing between working and nonworking siblings as caused by child labor would require the heroic assumption that work status is randomly assigned. Therefore, in our preferred specification, we condition our results on the number of younger and older siblings of each gender. Thus, we exploit the idiosyncratic component of the variation in work status that is not due to the child's birth order or to gender-specific birth-order effects. As a first step, we view this idiosyncratic variation as plausibly random.

However, parents are also likely to consider characteristics that are observable to them, but not to us, as a criterion to choose which of their children work. Parents likely make their decision on whether to send a child to work based on unobserved-to-us ability, in addition to gender-specific birth order and other observables. Similarly, parents could make child work decisions based on their children's physical health—the healthy-worker selection effect.[6]

Therefore, if we are to interpret differences in wellbeing between working and nonworking siblings as caused by child labor, we need to assess whether any such differences are simply the result of selection on unobservables. Oster (2019) formulates a test to tackle this possibility. Her method relies on the assumption that there is a proportional relationship between the characteristics defining both omitted and observed variables and that this relationship can be estimated and defined (De Luca, Magnus, & Peracchi, 2019). Oster's delta method answers the following question: how large would selection on unobservable characteristics (delta) have to be, relative to selection on observable characteristics, to explain away the effect of work? To estimate delta, we assume what the R-squared from an unbiased regression would look like. We estimate delta for values of R-squared ranging from 0.75 to 1. As we will see, in our setting, selection on unobservable characteristics would have to be extremely large relative to selection on gender-specific birth-order and other observables, such that we have firm reason to think our findings are not driven by selection.

Nevertheless, we err on the side of caution and apply two techniques to address the potential confounding effects of unobservable characteristics: Young (2019) randomization inference and Lewbel (2012) instrumental variables strategy. Young (2019) technique applies Fisherian randomization to provide exact tests of a null hypothesis of the treatment having no effect. Lewbel (2012) IV method works like a standard two-stage IV approach, with the exception that the first-stage exclusion restriction is generated by exogenous variables. Using the heteroskedasticity of these variables, Lewbel's method constructs internal instruments from the auxiliary equations' residuals. The latter are multiplied by each of the included exogenous variables in mean-centered form (Baum, Lewbel, Schaffer, & Talavera, 2012). Thus, the Lewbel approach achieves identification by having regressors that are uncorrelated with the product of heteroskedastic errors.

We standardized the measures of child psychosocial wellbeing by using the z-scores of each of the dependent variables, which we obtained by subtracting the mean value and dividing by the standard deviation. Therefore, the coefficients of the *Child Work* dummy variable can be interpreted as the difference in wellbeing, measured in standard deviations, between working and nonworking children.[7] We cluster standard errors at the household level throughout the analysis, thus allowing errors to be correlated between siblings.

4 | MAIN RESULTS

4.1 | Baseline

To set the stage, Figure 2 shows that, on average, working children display statistically significant lower levels of happiness, emotional wellbeing, self-efficacy and hopefulness. Working children are more stressed than nonworking children, although differences are not statistically significant. Working and nonworking children display similar levels of fear (being scared).

Panel A of Table 2 presents unconditional correlations between child labor and our dependent variables. The baseline results indicate that child labor has a negative and statistically significant relationship with happiness, hopefulness, emotional wellbeing and self-efficacy. These estimates are large: on average, work is associated with declines in psychosocial wellbeing of approximately 0.29–0.50 standard deviations.[8] We also find that work status is somewhat positively correlated with stress: the coefficient on the *Child Work* dummy is large and positive in Column (6), albeit imprecisely estimated.

4.2 | Accounting for potential confounders

In Panel B, we control for a wide range of potential confounders, which capture child-level and household-level characteristics that may be correlated with both child labor and child wellbeing. Including these variables does not alter our previous results: child labor is associated with lower levels psychosocial wellbeing of approximately 0.38–0.54 standard deviations for our first four measures. To preserve space, we report the coefficients and t-statistics for control variables in Appendix Table A1. Note that Panel B includes fewer observations than Panel A, as one control (monthly expenditure) is missing for some households. The results do not change if we drop monthly expenditure.

4.3 | Within-village estimates

In Panel C, we address the possibility that the unobserved factors that drive children into the workforce may vary between villages by including village fixed effects. This lets us capture all unobserved heterogeneity that is, to a first-order approximation, common to all children within a given village. For example, villages have varying cultural norms and geo-climatic conditions, which may correlate with both psychosocial wellbeing and child labor.

Exploiting only variation in child labor within villages, we found psychosocial wellbeing to be smaller by 0.21–0.42 standard deviations for working children for our first four measures. In Panel D, we control for both village fixed effects and the set of control variables included in Panels B and C—the results are again virtually unchanged. The coefficients and significance levels for the control variables from Panel D are shown in Appendix Table A2. Results from this model also suggest that working children might be less stressed.

4.4 | Estimates with household fixed effects

In this section, we control for unobserved heterogeneity between households by including a set of household dummies. These regressions include unobservable household characteristics that can potentially influence child wellbeing outcomes and the propensity to work. The regressions in Table 3 use a restricted sample in which there are at least two children surveyed from the same household (specification [2]). A key trade-off of focusing on smaller samples is that degrees of freedom are reduced. We therefore perform post-hoc power analyses, which indicate that, where we found significant results, we had sufficient statistical power to do so, despite the reduced sample size.[9]

Panel A of Table 3 shows the results with household fixed effects, while Panel B also includes additional controls (Table A3 in the Appendix shows the full results). Overall, we found consistent evidence of statistically significant effects. When the results are statistically insignificant, the signs and sizes of coefficient estimates are similar to those found above. The results in Panel A indicate that working children are significantly less happy, while the coefficient estimates of child labor in the remaining regressions are similarly sized to those previously found, though statistically

FIGURE 2 Psychological measures of child wellbeing, by work status. Notes: Capped spikes denote 95% confidence intervals. *p*-values for mean differences across working and nonworking children for each variable as follows: happy: 0.00; emotional wellbeing: 0.00; self-efficacy: 0.00; hope: 0.00; stressed: 0.93; scared: 0.58

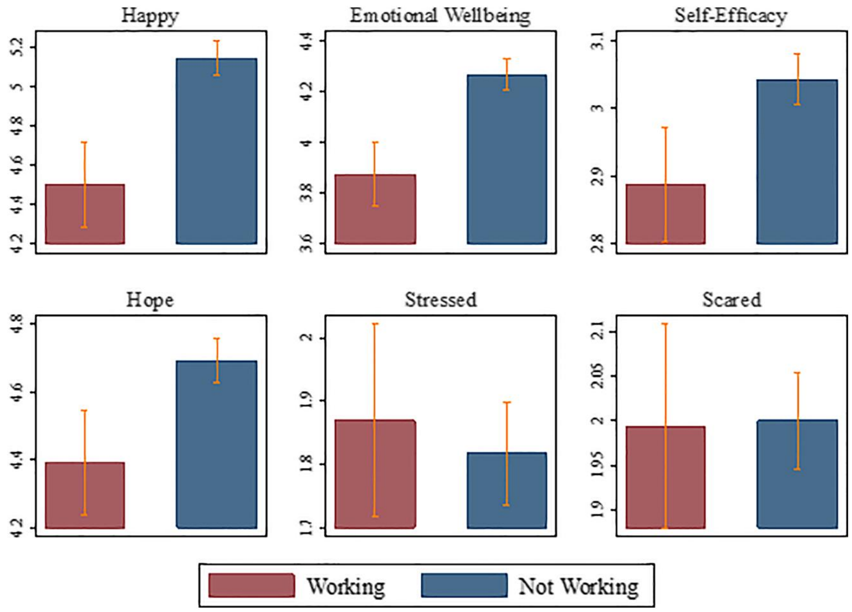

TABLE 2 Child labor and psychological outcomes

	(1) Happy	(2) Hopeful	(3) Emotional wellbeing	(4) Self-efficacy	(5) Scared	(6) Stressed
A. Baseline						
Child work	−0.50***	−0.32***	−0.46***	−0.29***	−0.01	0.05
	[−5.62]	[−3.53]	[−5.65]	[−3.43]	[−0.095]	[0.61]
Observations	947	947	947	947	947	939
R-squared	0.04	0.02	0.03	0.01	0.00	0.00
B. Controls						
Child work	−0.54***	−0.44***	−0.51***	−0.38***	0.04	−0.05
	[−5.16]	[−4.06]	[−5.22]	[−3.93]	[0.42]	[−0.50]
Observations	683	683	683	683	683	676
R-squared	0.11	0.07	0.09	0.06	0.03	0.05
C. Village FE						
Child work	−0.42***	−0.24***	−0.34***	−0.21***	0.02	−0.08
	[−5.38]	[−3.10]	[−4.60]	[−2.80]	[0.26]	[−0.99]
Observations	947	947	947	947	947	939
R-squared	0.30	0.26	0.23	0.29	0.06	0.11
D. Village FE + controls						
Child work	−0.47***	−0.33***	−0.39***	−0.25***	0.11	−0.25**
	[−4.68]	[−3.49]	[−4.22]	[−3.06]	[1.11]	[−2.20]
Observations	683	683	683	683	683	676
R-squared	0.33	0.32	0.29	0.39	0.10	0.16

Notes: Robust *t*-statistics in brackets. Controls included in Panels B and D: age, gender, school attendance, numbers of older brothers, younger brothers, older sisters, younger sisters, monthly spending and a wealth index. Errors are clustered over households. All specifications include a constant term.

Abbreviation: FE, Fixed effects.

***,** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE 3 Child labor and psychological outcomes with households fixed effects

A. Household FE	(1) Happy	(2) Hopeful	(3) Emotional wellbeing	(4) Self-efficacy	(5) Scared	(6) Stressed
Child work	−0.65***	−0.022	−0.34	−0.15	0.05	0.20
	[−3.39]	[−0.09]	[−1.60]	[−0.65]	[0.21]	[0.80]
Power	0.99	0.22	0.53	0.10	0.24	0.05
Observations	342	342	342	342	342	337
R-squared	0.54	0.51	0.53	0.51	0.45	0.37
B. Household FE + controls	**(1) Happy**	**(2) Hopeful**	**(3) Emotional wellbeing**	**(4) Self-efficacy**	**(5) Scared**	**(6) Stressed**
Child work	−0.64**	−0.059	−0.43**	−0.27	0.15	0.18
	[−3.18]	[−0.23]	[−2.04]	[−1.05]	[0.61]	[0.65]
Power	0.99	0.22	0.76	0.22	0.13	0.11
Observations	339	339	339	339	339	334
R-squared	0.56	0.53	0.57	0.54	0.49	0.40

Notes: Robust *t*-statistics in brackets. Controls include age, gender, school attendance, numbers of older brothers, younger brothers, older sisters, and younger sisters. Errors are clustered over households. All specifications include a constant term.

Abbreviation: FE, Fixed effects.

***,** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

insignificant. The results in Panel B are consistent with respect to happiness and suggest that working children exhibit statistically significantly lower levels of emotional wellbeing.

The results in Table 3 allow us to introduce a richer set of controls than those in Table 2. However, it is also intuitively appealing to study differences in child wellbeing in households with more than one child and in which one child works, while others do not. Thus, in our preferred specifications, we compare wellbeing for working children to the wellbeing of their nonworking siblings. In doing so, we focus our attention on within-household variation only. The results are summarized in Table 4. We estimate an OLS model, including household-specific dummies. Panel A includes only household fixed effects, while Panel B has additional child-level controls (see Table A4 in the Appendix for the full results). Panel A suggests that working children are less happy, while Panel B suggests that working children are both statistically less happy and have statistically lower levels of emotional wellbeing than their nonworking siblings. The coefficient estimates suggest that, on average, working children experience approximately 0.65 standard deviation lower happiness and 0.45 standard deviation lower emotional wellbeing. The coefficient estimates attached to the remaining variables are similarly sized to those previously found, though statistically insignificant.

4.5 | Assessing the extent of selection on unobservable characteristics

Panel B of Table 4 conditions the estimates on the number of younger and older siblings of each gender. Therefore, the coefficients of *Child Work* reflect the differences in wellbeing between a working sibling and a nonworking sibling, from the same family, that are *not* due to birth order, gender or gender-specific birth order. Thus, Panel B exploits only the idiosyncratic component of the variation in work status that is not due to the above factors. The effect of *Child Work* can be viewed as causal under the assumption that work status is randomly assigned, conditional on observables.

TABLE 4 Child labor and psychological outcomes *within* households

A. Household FE						
	(1) Happy	(2) Hopeful	(3) Emotional wellbeing	(4) Self-efficacy	(5) Scared	(6) Stressed
Child work	−0.65***	−0.02	−0.34	−0.15	0.05	0.20
	[−3.43]	[−0.090]	[−1.61]	[−0.66]	[0.21]	[0.80]
Power	0.99	0.20	0.56	0.09	0.22	0.06
Observations	108	108	108	108	108	106
R-squared	0.65	0.52	0.59	0.57	0.45	0.42
B. Household FE + controls						
	(1) Happy	(2) Hopeful	(3) Emotional wellbeing	(4) Self-efficacy	(5) Scared	(6) Stressed
Child work	−0.66***	−0.16	−0.45**	−0.31	0.19	0.16
	[−3.48]	[−0.62]	[−2.36]	[−1.25]	[0.70]	[0.56]
Power	0.99	0.11	0.83	0.34	0.10	0.17
Observations	107	107	107	107	107	105
R-squared	0.68	0.60	0.66	0.64	0.52	0.44

Notes: Robust *t*-statistics in brackets. Controls include age, gender, school attendance, numbers of older brothers, younger brothers, older sisters, younger sisters, monthly spending and a wealth index. Errors are clustered over households. All specifications include a constant term.

Abbreviation: FE, Fixed effects.

***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

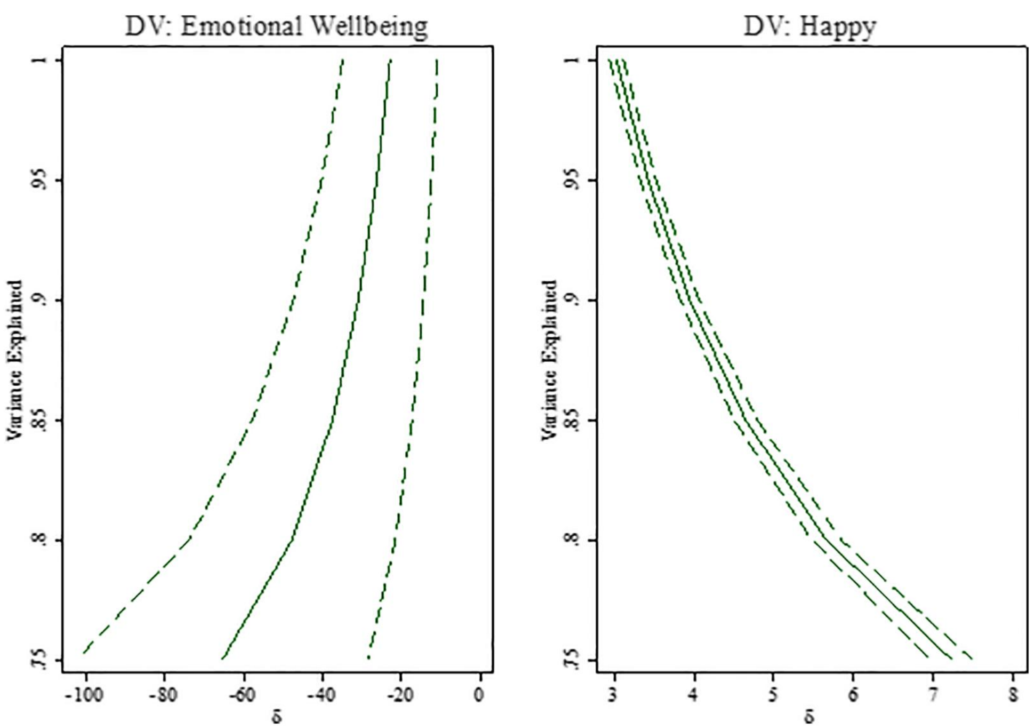

FIGURE 3 Estimates of δ (Oster, 2019). Notes: Dashed lines are the upper and lower ends of the 95% confidence intervals for δ. Jackknife variance estimates for δ are obtained by excluding one household at a time

We examine the sensibility of this assumption with Oster (2019) test. We use this method to determine how large a selection on, say, ability (and other unobservable characteristics) would have to be, relative to selection on observable characteristics, to explain away the effect of *Child Work*. We perform this exercise for the two outcomes of interest that we found to be significantly correlated with *Child Work* within families: *Happy* and *Emotional Wellbeing* (see Figure 3), using within-household specifications with controls analogous to the ones used in Table 4.

Figure 3 shows the share of the variance explained on the vertical axis, and Oster's δ on the horizontal axis. δ is the size of the selection on unobservables, relative to selection on observables, which would make *Child Work* insignificant. In the right panel of Figure 3, even assuming our model could explain 100% of the variation in the data, selection on unobservables would have to be three times as large as selection on observables for *Child Work* to have no discernible effect on *Happy*. If instead we assumed our model could explain 75% of the variation, the resulting value of δ would be approximately 7.

The pattern observed in the left side of the panel, where *Emotional Wellbeing* is the dependent variable, is even starker. A very large $\delta = -22.95$ is required to make *Child Work* insignificant, even assuming 100% of the variance can be explained.

In sum, for selection on unobservables to explain away our results, it would have to be at least three times larger (for *Happy*) and at least 22 times larger (for *Emotional Wellbeing*) than selection on observables. These are very large and thus implausible numbers when taken independently; it is also worth noting that the two sets of numbers have opposite signs. This implies that selection on unobservables would have to be negatively correlated with selection on observables ($\delta < 0$) in the case of one of our dependent variables (*Emotional Wellbeing*), but positively correlated with selection on observables ($\delta > 0$) in the case of *Happy*, our other dependent variable. This seems rather unlikely, thus, we are confident that selection on ability and other unobservables are not driving our results. Nevertheless, we err on the side of caution and, in what follows, attempt to correct for potential omitted variable bias.

4.6 | Addressing potential omitted variable bias

A key trade-off of focusing on households in which at least one child works and at least one does not, as in Table 4, is that the size of the sample may not be large enough to support robust inference. The test statistics that we report rely on distributional assumptions that hold only asymptotically and may thus not be valid in our smaller samples. Additionally, there could be omitted variables which correlate systematically with the treatment status: for example, if high-ability children are both less happy and more likely to work, the *Child Work* dummy may be picking up the effect of ability rather than work.

To tackle these issues, we implement randomization inference estimates, which produce close-to-exact test statistics in smaller samples without making any distributional assumptions, and allow us to check whether we are in fact picking up the effect of work, by repeatedly resampling the treatment assignment.[10] We perform 2000 permutations[11] using Young (2019) methodology, while stratifying at the household level[12], to determine the distribution of the test statistic under the null hypothesis of no effect through resampling. Effectively, this enlarges the size of the sample, making significance levels more sensitive to smaller departures from the null hypothesis. This is particularly relevant in our case given that the within-household regressions rely on a smaller sample. Young (2019) randomization inference technique approximates exact tests of a null hypothesis of the treatment having no effect regardless of sample size, regression design or characteristics of the disturbance term. The results of this exercise are presented in Figure 4. As a point of reference, the red lines in the figure correspond to the point estimates from Table 3, Panel B.

Regarding the happiness and emotional wellbeing results, Figure 4 shows that recalculating the test statistic after undertaking 2000 permutations provides *p*-values that allow us to reject the null hypothesis of no child-labor effect. That is, working children are again found to be less happy and have lower levels of emotional wellbeing, even within the same household as nonworking children. This is a robust result which holds with close-to-exact statistics, and was therefore not driven by the reduced sample sizes in Table 4. The results attached to self-efficacy are consistent, although the associated *p*-value shows statistical significance at the 10% level. The remaining coefficient estimates are not statistically significant at conventional levels.

We also deal with potential omitted variable bias with an instrumental variables approach. However, estimating an adequately identified local average treatment effect that reaches beyond the within-family estimates is empirically problematic. The ideal instrument should be a root cause of child labor but be otherwise uncorrelated with child wellbeing. In practice, it is unlikely that any phenomenon that pushes children to work does not also affect their wellbeing through some other channel. In the absence of external instruments or randomized exogenous shocks, we

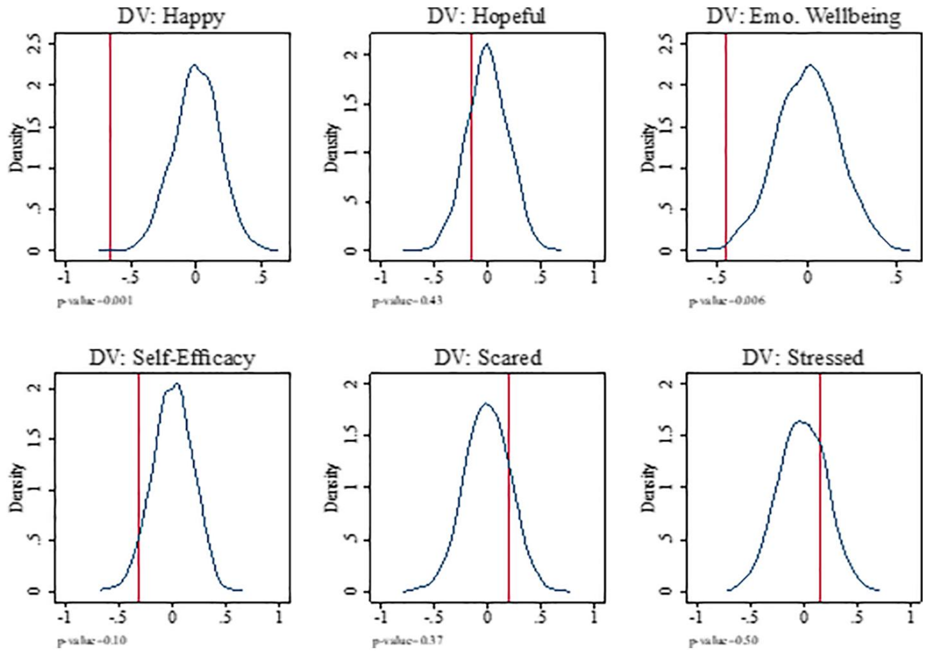

FIGURE 4 Randomization inferences. Notes: Randomization inferences are calculated using Young (2019) method from the within-household regressions

TABLE 5 Causal inferences of child labor and psychological outcomes

	(1) Happy	(2) Hopeful	(3) Emotional wellbeing	(4) Self-efficacy	(5) Scared	(6) Stressed
A. Lewbel + controls & village fixed effects						
Child work	−0.67***	−0.44***	−0.55***	−0.44***	0.34**	−0.33**
	[−4.18]	[−3.47]	[−4.24]	[−3.53]	[2.32]	[−2.14]
Observations	683	683	683	683	683	676
First stage F-stat	25.8	25.8	25.8	25.8	25.8	26.4
Hansen J *p*-value	0.26	0.0049	0.14	0.58	0.31	0.28
R-squared	0.32	0.32	0.29	0.39	0.10	0.16
B. Lewbel + controls within-household effects						
Child work	−0.69***	−0.026	−0.56***	−0.26	0.064	0.16
	[−5.17]	[−1.33]	[−3.59]	[−1.36]	[0.29]	[0.78]
Observations	107	107	107	107	107	105
R-squared	0.68	0.60	0.65	0.64	0.51	0.44

Notes: Robust t-statistics in brackets. Controls include age, gender, school attendance, numbers of older brothers, younger brothers, older sisters, younger sisters, monthly spending and a wealth index. Errors are clustered over households. First stage F-statistic refers to Cragg-Donald Wald F statistic. All specifications include a constant term.

***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

attempt to further address causality using the approach proposed by Lewbel (2012). His approach is to use a two-stage-least squares (2SLS) strategy that relies on internally constructed heteroskedasticity-based instruments.

The results are presented in Table 5. Panel A includes all controls and village fixed effects, while Panel B includes all controls and household fixed effects. An advantage of the Lewbel approach is that it overidentifies the first-stage regression, which allows us to estimate Hansen tests for the validity of over-identifying restrictions. The Hansen statistics in Panel A of Table 5 suggest that the instruments do a sound job in all columns, except for Column 2.

First-stage *F*-statistics from Panel A are approximately 26, suggesting again the instrument set strongly predicts the endogenous regressor of interest, *Child Work*.[13] The full Lewbel results are shown in Appendix Table A5.

Altogether, the results in Table 5 are supportive of the findings above. The panels exhibit evidence to suggest that working children are less happy and have lower levels of emotional wellbeing. Coefficient sizes are similar across panels. Panel A also shows evidence suggesting that child work results in lower levels of self-efficacy and higher levels of fear. Interestingly, Panel A suggests that working children are less stressed, perhaps because they feel that they are contributing to the household. This interpretation warrants further analysis in future studies. Overall, the magnitude of the estimated effects is close to those found in the previous tables.

5 | FURTHER RESULTS

5.1 | Exploring heterogeneity in the child labor - psychosocial wellbeing relationship

We examine whether the relationship between child labor and psychosocial wellbeing is contingent upon the child's gender and whether they are regularly attending school using interactions. Within-household regressions, available upon request, show that neither gender nor school attendance significantly change the underlying relationships.

In another exercise, we examine the impact of child labor on the various indicators used to create the three aggregate mental health measures summarized in Table 2—hopefulness, emotional wellbeing and self-efficacy. This allows us to isolate the indicators that are potentially most affected by child labor. To do so, we estimate full-sample and *within*-household regressions (see Appendix A, Tables A6 and A7). Table A7, which summarizes the results from within-household regressions, shows that after controlling for unobserved characteristics, certain indicators are potentially driving the overall results. We find that child workers may feel less hopeful because they consider that they are doing worse than other children. Child workers have lower levels of emotional wellbeing, not only because they are less happy, but also because they are less likely to feel that they have something important to contribute and feel less able to manage their responsibilities.

5.2 | Child labor's effect on a composite index of child psychosocial wellbeing

We recognize that psychosocial wellbeing is a latent variable which relates to holistic mental health, incorporating multiple dimensions. Having a positive sense of wellbeing, feeling happy and hopeful, being able to do things for oneself, and being free from anxiety, including feelings of being scared and stressed, represent important dimensions of overall psychosocial wellbeing. These components of psychosocial wellbeing were employed individually in the analysis to ascertain which ones are most affected by child labor. Here, a composite index of psychosocial wellbeing is constructed. The six different measures of psychosocial wellbeing are related to each other since they capture similar aspects of the underlying latent psychosocial wellbeing variable. This is reflected by their covariance. The composite index is therefore constructed using weights derived from principal components analysis (PCA). The use of the index also helps to address concerns regarding multiple hypothesis testing, since we are now looking at the effect of child labor on a single dependent variable.

Figure 5 provides the kernel density functions of the PCA-weighted wellbeing index for working versus nonworking children. The functions differ across the two groups with a larger proportion of working children having lower index scores than children who are not working.

The composite index is also employed as a dependent variable in our regression analysis. The results pertaining to the impact of child labor across the different model specifications are summarized in Figure 6. They once again suggest a negative impact of working on child psychosocial wellbeing. The coefficient on the child labor variable is always negative, statistically significant, as well as stable across the different model specifications. Coefficients vary in size from between -0.5 and -1.

5.3 | Falsification exercise: Household chores and psychosocial wellbeing

The introduction argues that child labor potentially affects psychological health through a variety of mechanisms. Some mechanisms, such as lack of time for recreation/rest and lack of time with families, could be related to many types of

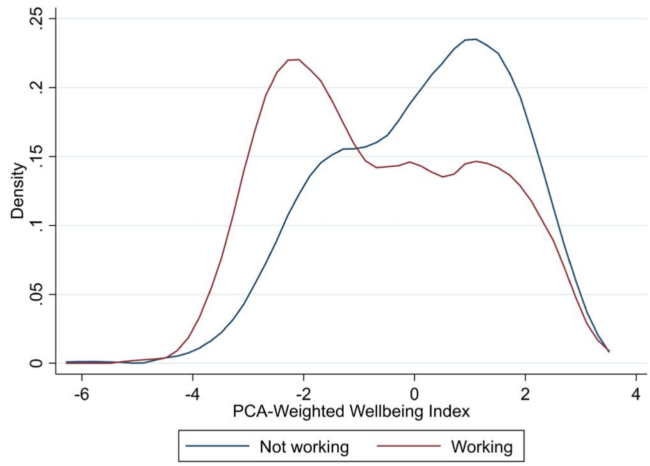

FIGURE 5 Kernel Density functions of principal components analysis (PCA)-weighted Wellbeing Index, working versus nonworking children

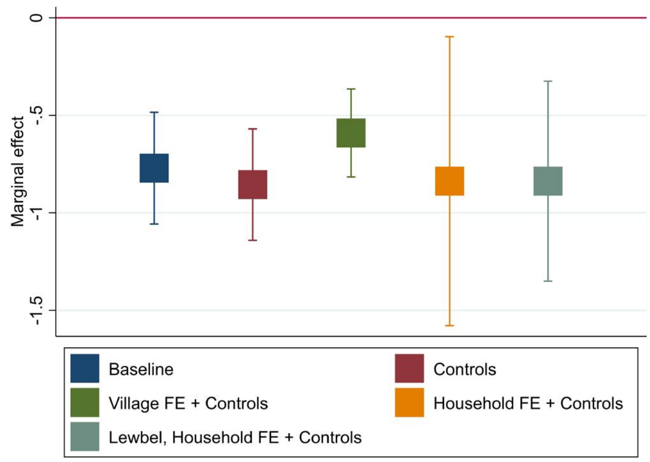

FIGURE 6 Marginal effects of child labor on the principal components analysis (PCA)-weighted psychosocial wellbeing index with 95% confidence intervals. Notes: Marginal effects estimated from model specified in Section 5. Confidence intervals estimated at the 95% level. All estimates use standard errors clustered over households. All specifications include a constant term

extracurricular activities. Other mechanisms, such as lack of autonomy over work conditions and a conflictive role of the child worker with their family or community, are more likely to stem from work. While it is difficult to directly isolate the mechanisms that potentially lead to worse psychological health outcomes, we can try to rule out the role of other nonlabor extracurricular activities to verify whether it is indeed child labor that negatively affects children, or simply being occupied by any other time-consuming tasks, whether labor-related or not.

We do this by testing the relationship between psychological wellbeing and a dummy variable equal to 1 if the child undertakes a given household chore. The survey asked children if during the past week they undertook any of the following tasks: (i) shopping for household, (ii) repairing any household equipment, (iii) cooking, (iv) cleaning utensils/house, (v) washing clothes, and/or (vii) caring for children/old/sick. Chores are likely to represent the biggest out-of-school (nonplay) activity, with virtually all children performing at least one household chore per week.[14] Our analysis is based on comparing children that undertake a given task versus others that do not, within the same household, such that we can capture the differential effect on observationally similar children of undertaking a household chore when a sibling does not.

Table 6 shows estimates of *within*-household regressions. For ease of exposition, each cell shows coefficient estimates from separate regressions. We show 36 coefficients; each coefficient captures the correlation between a

TABLE 6 Household chores and child wellbeing, within-household regressions

Chore/dep. Var.:	Happy	(1) Hopeful	(2) Emotional wellbeing	(3) Self-efficacy	(4) Scared	(5) Stressed	(6)
Shopping	Coeff.	0.21	0.25	0.34	0.55	0.061	−0.20
	t-stat	[0.74]	[0.87]	[1.15]	[1.67]	[0.23]	[−0.67]
	Obs.	70	70	70	70	70	70
	R^2	0.65	0.57	0.72	0.73	0.57	0.59
Repairing	Coeff.	0.031	0.064	0.13	−0.059	0.37*	0.078
Household	*t*-stat	[0.20]	[0.38]	[0.73]	[−0.34]	[1.68]	[0.37]
Equipment	Obs.	186	186	186	186	186	184
	R^2	0.61	0.61	0.55	0.59	0.52	0.43
Cooking	Coeff.	0.16	0.13	0.023	−0.18	−0.032	0.18
	t-stat	[0.53]	[0.39]	[0.074]	[−0.58]	[−0.12]	[0.72]
	Obs.	191	191	191	191	191	190
	R^2	0.53	0.52	0.55	0.60	0.50	0.44
Cleaning	Coeff.	0.46	0.26	0.44	0.42	−0.20	−0.14
	t-stat	[1.63]	[0.75]	[1.59]	[1.20]	[−0.69]	[−0.61]
	Obs.	193	193	193	193	193	192
	R^2	0.52	0.48	0.56	0.57	0.50	0.46
Washing	Coeff.	0.15	0.31	0.32	0.22	−0.047	−0.036
Clothes	t-stat	[0.75]	[1.22]	[1.39]	[0.89]	[−0.21]	[−0.17]
	Obs.	198	198	198	198	198	196
	R^2	0.54	0.55	0.57	0.56	0.51	0.42
Caring for	Coeff.	−0.075	0.046	0.47*	0.21	0.44**	0.42
Children/Old/	t-stat	[−0.33]	[0.20]	[1.96]	[0.78]	[2.20]	[1.57]
Sick	Obs.	118	118	118	118	118	116
	R^2	0.54	0.56	0.58	0.57	0.55	0.42

Notes: Robust t-statistics in brackets. Controls include age, gender, school attendance, numbers of older brothers, younger brothers, older sisters, younger sisters, monthly spending and a wealth index. Errors are clustered over households. Each row summarizes results from separate regressions. All specifications include a constant term.

***,** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

psychosocial outcome *Y* and performing a given task *T*. We find no evidence to suggest that household chores are at all likely to lead to lower levels of happiness, hopefulness, emotional wellbeing or self-efficacy. Indeed, Column 3 suggests that if a child cares for others in the household, if anything, he or she is *more* likely to feel higher levels of emotional wellbeing. Interestingly, Column 5 uncovers evidence that repairing household equipment and caring for others is likely to make children more scared. This may result from children using dangerous tools when repairing goods and dealing with illness or death when caring for others.

Overall, these results help us conclude that it is not chores, but work, that likely leads to lower levels of happiness and emotional wellbeing. While data to delve deeper into the mechanisms may not be available, one could speculate that the results stem from the conditions pertaining to performing work outside the home relative to undertaking household chores inside the home. Household chores inside the home are potentially performed in reasonably safe conditions or under adult supervision. Conversely, work outside the home is potentially more hazardous due to surrounding conditions and lack of supervision.

6 | DISCUSSION

Mental health is often a neglected health issue in developing countries. Although data on the mental health of children are rarely collected, the WHO estimates that as many as one in five children and adolescents around the world experience mental disorders, with depression alone accounting for 4.3% of the global burden of disease (WHO, 2013). To study this important issue, we collected a new dataset comprised of 947 children aged 12–18 from 750 households in 20 villages across five districts in Tamil Nadu. The data were collected from June to September 2018, which coincides with mid-to-late summer, when children are most likely to work. Therefore, our survey may overestimate the proportion of working children relative to surveys conducted in winter periods. The survey allows for a holistic approach to the analysis of child wellbeing by accounting for levels of happiness, hope, emotional wellbeing, self-efficacy, fear and stress.

Our econometric approach employed a variety of techniques, some utilized village fixed effects, while others used household-level fixed effects. Our preferred identification strategy is to compare two siblings in the same household and condition our results on child sex and the number of younger and older siblings of each gender, in doing so, we argue that the two children are statistically similar.

We document a robust negative association between child labor and psychosocial wellbeing. We find that, on average, working children experience approximately 0.65 standard deviation lower happiness and 0.45 standard deviation lower emotional wellbeing. We examined the sensitivity of our identifying assumption to selection on unobservables, such as ability and physical health, and found that selection would have to be implausibly large to explain away our results. We complement those findings with randomization inferences and Lewbel-IVs and argue that our results can be interpreted as causal.

There are several limitations that need to be considered when interpreting our results. We unfortunately cannot discern any long-term consequences of child labor on health from our data. To do so, we would need a longitudinal study, which would also allow us to apply panel data techniques that help us avoid restricting our sample, in our preferred specification, only to households with siblings. The regressions in Table 3 use a restricted sample in which there are at least two children surveyed from the same household. In Table 4 we further restrict the sample to test what happens when one child works, but not the other. Our sample drops from 947 children in Table 2 to 339 and 108 in Table 3 and 4, respectively. Restricting the sample size results in larger confidence intervals, thus statistically significant results will occur only when there are large differences between working and nonworking children: we lose statistical power. This means that some of the discrepancies in statistical significance between Table 2 and 4 could be due to sample size, rather than because of the specification. We acknowledge this limitation and only discuss the statistically significant findings, which have enough power.

Another limitation is that the child labor variable does not capture how many hours children work for.[15] This limits our ability to ascertain differences in psychological wellbeing stemming from varying intensity of labor. This is a potential avenue of future work. We use a dummy variable because we opted to adhere to the ILO's classification. In so doing, however, we also do not distinguish between different labor activities (see Table 1). This is potentially problematic because some activities may be hazardous, which could presumably lead to worse effects on physical, and subsequently, mental health. Notwithstanding, making assumptions about certain activities being significantly more hazardous than others can also be problematic. For example, it is understood that children working in agriculture are disproportionately exposed to hazardous activities such as (i) long periods of stooping and repetitive movements, (ii) carrying heavy loads over long distances, (iii) work in extreme temperatures and without access to safe water, and (iv) exposure to chemicals, organic dusts and biological hazards (ILO, 2011). However, children working in construction may be exposed to similar types of activities, while those working in paid employment or as domestic laborers may be exposed to violence and abuse (ILO, 2011). Therefore, it is not necessarily the type of activity, but the conditions in which children work that can make that work hazardous. Moreover, assuming that work that is physically more demanding is the mechanism through which child work affects mental health, ignores other potential channels, such as added stress that can be associated with work at an early age. For instance, by having to work, children may feel pressure or see themselves as different to other children.

By adopting a more general definition of child labor, we avoid making any assumptions about how the nature of different types of work affects mental health. However, the potential effect of different types of labor activities on child mental health remains an important avenue of future work. Posso (2019) studied the (physical) health consequences of child labor in Peru using a specialized survey that focused on hazardous activities, such as heavy lifting or working with sharp tools. Researchers interested in assessing the mental health consequences of such work should consider using surveys that focus on work activities, rather than work classifications.

Another important limitation is that the survey did not ask children whether they are working in more than one activity. We understand that there is significant seasonality in child labor. As a result, we undertook the survey during a period in which children are more likely to work, but also during a period where this work is more likely to be in agriculture. We cannot say with certainty, however, how many activities working children were involved in.

7 | CONCLUSION

Child labor remains a major social problem in India, as well as in much of the developing world. The phenomenon is associated with poor physical health outcomes and educational opportunities. We add to this body of evidence by identifying a statistically significant and negative relationship between child labor and child psychosocial wellbeing. We argue that this association is likely to be causal.

Combatting the psychological consequences of child labor will require policymakers to treat the root causes of child labor. However, this societal problem is difficult to address from a policy perspective. Banning child labor can have adverse impacts on child wages, which may lead to an increase in child labor to compensate for the fall in income. Therefore, other types of interventions to deal with the psychological consequences of child work may be warranted. Family education programs on how to identify mental health issues in children and adolescents are potentially required. Schools can also play a role, as can scaling up mental health services including cognitive behavioral therapy and other treatments, particularly in rural areas. Since poorer mental health of children is related to other adverse outcomes such as lower educational achievement, substance abuse, violence and poor reproductive health, early treatment is crucial and can have considerable returns (Patel et al.,).

ACKNOWLEDGMENTS

The authors are grateful for helpful feedback from seminar participants at Deakin University. They are also grateful to Suresh Appukuttan for research assistance during fieldwork and data collection. The data used in this article will be made available online upon publication via the RMIT University Data Repository Website.

CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ORCID

Alberto Posso https://orcid.org/0000-0003-4226-7072

ENDNOTES

[1] See Ibrahim, Abdalla, Jafer, Abdelgadir, and de Vries (2018) for a systematic review of the child labor and health literature.

[2] In employing a sibling-based identification strategy, we also follow in the footsteps of Bharadwaj, Lakdawala, and Li (2020), who uses a sibling-based difference-in-differences approach to study the consequences of child labor legislation in India; see footnote 3 below.

[3] Thanjavur district is semi-arid but with a delta in a relatively wet zone. Cuddalore district is vulnerable to natural hazards, such as cyclones and is characterized by a flood delta and semi-arid climatic conditions. These two districts constitute about 40% of the entire State of Tamil Nadu. Villages selected from the districts proportionately represented wet and dry areas in the State. The selection of sample villages was done in consultation with district-level officials using a purposive sampling approach to adequately capture agro-climatic differences.

[4] Note that some children may not have been present because they may migrate during the summer season to areas where they can find job opportunities, particularly in brick, matchbox and cracker making units. The proportion of working children in our sample is higher than the proportion of working children in India's rural areas.

[5] For a similar approach see LaFave and Thomas (2017).

[6] While we do have a measure for physical health in our dataset, its direct inclusion into the models is problematic because physical health is endogenous. As explained in Angrist and Pischke (2008), introducing "bad controls" of this type can lead to additional sources of bias. For completeness, we calculated weight-for-age *Z*-scores and introduced them as control variables in the within-household regressions. The results of this exercise, available upon request, are consistent with those reported below.

[7] Note that we collect our measures using the validated scales designed by the authors of the relevant measures, and only standardize the variables for the analysis. Thus, our standardization does not affect the psychometric properties of the measures.

[8] These numbers correspond to the coefficients from Columns (1) and (4) of Panel A of Table 2.

[9] It is worthwhile to highlight that when we do not find statistically significant results, we have low power. Therefore, when results are insignificant, we cannot be certain that a statistically insignificant effect is the "true" effect. This means that a larger sample size could potentially give results that are similar to those presented in Table 2.

[10] The intuition dates back to Fisher's (1935) tea tasting experiment. For any given binary treatment, each observational unit can either be treated or not treated; the set of all potential treatment allocations is thus known. Whereas a *t*-test compares the observed test statistic to a Student's t-distribution, randomization inference compares the observed test statistic to the distribution of test statistics that could have been obtained under all possible treatment assignments. Comparing the observed test statistic to the distribution of all possible test statistics therefore yields an exact *p*-value, even in smaller samples.

[11] Young (2019) shows that randomization inference estimates are stable beyond 2000 draws.

[12] This approach was developed for randomized control trials. Using binary treatment variables, Heß (2017) shows that Young's method works well with binary treatment variables but that the "logic of randomization inference equally applies to other data generating processes… [such as] continuous treatments" (p. 633).

[13] Hansen and first stage F-statistics are not reported when household fixed effects are included because instrument proliferation (number of instruments greater than the number of groups) vitiates the tests (Roodman, 2009). The results in Panel C, however, do provide us with reasonable degree of confidence about the validity of our instruments and general findings.

[14] We do not run regressions using a dummy equal to 1 if children undertake at least one chore per week because of this reason—99% of children undertake at least one chore.

[15] We presume that obtaining reliable data on hours of work may be difficult.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Feeny S, Posso A, Skali A, Jyotishi A, Nath S, Viswanathan PK. Child labor and psychosocial wellbeing: Findings from India. *Health Economics*. 2021;1–27. https://doi.org/10.1002/hec.4224

APPENDIX

Additional figures and tables

Table A.1 Control variables from Panel B of Table 3 in the main text

	(1) Happy	(2) Hopeful	(3) Emotional wellbeing	(4) Self-efficacy	(5) Scared	(6) Stressed
Age	−0.041**	0.018	0.043**	0.0073	0.019	0.031
	[−2.03]	[0.90]	[2.12]	[0.36]	[1.00]	[1.49]
Girl	−0.017	0.038	−0.064	−0.053	0.11	−0.21***
	[−0.22]	[0.50]	[−0.83]	[−0.70]	[1.50]	[−2.60]
N. Older brothers	0.0028	0.076	0.050	0.042	−0.017	−0.023
	[0.055]	[1.54]	[1.04]	[0.87]	[−0.42]	[−0.30]
N. Older sisters	−0.074	0.015	−0.016	0.045	−0.023	−0.13***
	[−1.17]	[0.23]	[−0.29]	[0.69]	[−0.48]	[−2.61]
N. Younger brothers	0.015	0.11*	0.089	0.033	0.027	0.030
	[0.20]	[1.67]	[1.15]	[0.45]	[0.36]	[0.40]
N. Younger sisters	−0.15*	−0.084	−0.25***	−0.052	0.092	−0.16*
	[−1.89]	[−1.13]	[−3.07]	[−0.65]	[1.09]	[−1.89]
School attendance	−0.12	0.035	0.21*	0.030	0.37***	0.27*
	[−0.84]	[0.30]	[1.68]	[0.21]	[3.32]	[1.94]
Wealth index	−0.046**	−0.017	0.040	−0.033	0.032	0.074***
	[−2.39]	[−0.84]	[1.65]	[−1.42]	[1.58]	[3.81]
Monthly expenditure ('000 INR)	0.033***	0.031***	0.024**	0.030***	−0.016***	−0.0024
	[4.11]	[2.67]	[2.54]	[2.90]	[−2.72]	[−0.36]
Constant	0.54	−0.65*	−0.97**	−0.40	−0.52	−0.43
	[1.42]	[−1.68]	[−2.58]	[−1.03]	[−1.52]	[−1.11]

Notes: Robust t-statistics in brackets. Errors are clustered over households.

*****,** and * denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.2 Control variables from Panel D of Table 3 in the main text.

	(1) Happy	(2) Hopeful	(3) Emotional wellbeing	(4) Self-efficacy	(5) Scared	(6) Stressed
Age	−0.0023	0.056***	0.080***	0.052***	0.0092	0.018
	[−0.12]	[3.26]	[4.31]	[3.02]	[0.48]	[0.87]
Girl	−0.075	−0.023	−0.11	−0.11*	0.12*	−0.16*
	[−1.08]	[−0.33]	[−1.51]	[−1.76]	[1.65]	[−1.94]
N. Older brothers	−0.021	0.034	0.014	0.0076	0.00031	0.0054
	[−0.47]	[0.87]	[0.35]	[0.19]	[0.0076]	[0.077]
N. Older sisters	−0.11**	−0.037	−0.062	−0.0014	−0.0015	−0.079
	[−2.07]	[−0.69]	[−1.33]	[−0.026]	[−0.029]	[−1.50]
N. Younger brothers	0.018	0.099	0.088	0.033	0.018	0.085
	[0.25]	[1.58]	[1.22]	[0.57]	[0.25]	[1.14]
N. Younger sisters	−0.15**	−0.086	−0.26***	−0.046	0.10	−0.17**
	[−2.03]	[−1.35]	[−3.51]	[−0.73]	[1.21]	[−1.98]
School attendance	0.078	0.29***	0.45***	0.29**	0.35***	0.064
	[0.60]	[2.95]	[4.41]	[2.49]	[3.01]	[0.45]
Wealth index	−0.056***	−0.025	0.040**	−0.033**	0.040**	0.071***
	[−3.31]	[−1.58]	[2.29]	[−2.14]	[2.09]	[3.57]
Monthly expenditure (‘000 INR)	0.013***	0.0091	0.0022	0.0048	−0.011	0.012*
	[2.83]	[1.33]	[0.33]	[1.09]	[−1.51]	[1.66]
Constant	0.49	−0.83**	−1.33***	−0.76*	−0.67*	−0.68*
	[1.24]	[−2.25]	[−3.18]	[−1.94]	[−1.65]	[−1.71]

Notes: Robust t-statistics in brackets. Errors are clustered over households.

***** and * denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3 Control variables from Panel B of Table 4.

	(1) Happy	(2) Hopeful	(3) Emotional wellbeing	(4) Self-efficacy	(5) Scared	(6) Stressed
Age	−0.000058	0.034	0.056*	0.031	−0.038	0.057*
	[−0.0019]	[0.97]	[1.77]	[0.79]	[−1.04]	[1.68]
Girl	−0.042	0.035	−0.058	−0.22*	0.23*	−0.12
	[−0.34]	[0.31]	[−0.53]	[−1.82]	[1.93]	[−0.89]
N. Older brothers	0.069	0.13	0.17**	0.17*	−0.076	0.034
	[0.81]	[1.44]	[2.01]	[1.89]	[−0.81]	[0.37]
N. Older sisters	−0.14*	0.075	0.18**	0.11	0.073	−0.0063
	[−1.69]	[0.84]	[2.09]	[1.23]	[0.78]	[−0.069]
N. Younger brothers	0.081	0.064	0.014	0.12***	−0.097*	−0.12***
	[1.52]	[1.11]	[0.34]	[3.09]	[−1.70]	[−2.91]
N. Younger sisters	−0.045	−0.093	−0.043	−0.10	0.079	0.15
	[−0.37]	[−0.66]	[−0.34]	[−0.67]	[0.42]	[0.79]
School attendance	−0.12	0.20	0.32*	0.00097	0.38**	0.28
	[−0.59]	[1.17]	[1.77]	[0.0044]	[2.02]	[1.33]
Constant	0.35	−0.64	−1.06*	−0.37	0.15	−1.15*
	[0.62]	[−1.06]	[−1.91]	[−0.52]	[0.23]	[−1.85]

Notes: Robust z-statistics in brackets. Errors are clustered over households.

***** and * denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.4 Control variables from Panel B of Table 5.

	(1) Happy	(2) Hopeful	(3) Emotional wellbeing	(4) Self-efficacy	(5) Scared	(6) Stressed
Age	0.045	0.16***	0.11**	0.14**	−0.046	0.019
	[1.02]	[2.71]	[2.19]	[2.32]	[−0.71]	[0.32]
Female	0.10	−0.053	−0.16	−0.27	0.034	−0.058
	[0.75]	[−0.29]	[−0.89]	[−1.25]	[0.15]	[−0.23]
N. Older brothers	−0.12	0.13	−0.042	0.067	0.13	0.063
	[−0.93]	[0.82]	[−0.32]	[0.42]	[0.72]	[0.35]
N. Older sisters	−0.14	0.043	0.091	0.042	0.022	−0.16
	[−0.91]	[0.28]	[0.89]	[0.34]	[0.17]	[−1.10]
N. Younger brothers	−0.056	0.24	−0.085	−0.11	−0.057	−0.037
	[−0.28]	[0.94]	[−0.50]	[−0.47]	[−0.21]	[−0.18]
N. Younger sisters	−0.053	−0.065	0.11	0.12	−0.0098	0.14
	[−0.35]	[−0.31]	[0.75]	[0.54]	[−0.030]	[0.44]
School attendance	−0.26	0.22	0.092	0.094	0.72**	−0.30
	[−0.94]	[0.69]	[0.41]	[0.28]	[2.33]	[−0.76]
Constant	0.0077	−2.62***	−1.52*	−1.83*	−0.016	−0.063
	[0.0094]	[−2.79]	[−1.78]	[−1.78]	[−0.014]	[−0.060]

Notes: Robust z-statistics in brackets. Errors are clustered over households.

***** and * denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.5 Additional results: Full Lewbel results (Table 5).

Dep. Var:	(1) Happy	(2) Hopeful	(3) Emotional wellbeing	(4) Self-efficacy	(5) Scared	(6) Stressed
Child work dummy	−0.53***	−0.14	−0.53***	−0.40*	0.15	0.054
	[−3.65]	[−0.60]	[−3.11]	[−1.81]	[0.79]	[0.24]
Age	−0.015	0.027	0.042	0.0027	−0.031	0.067
	[−0.42]	[0.69]	[1.20]	[0.061]	[−0.80]	[1.62]
Girl	−0.060	0.18	0.0085	−0.14	0.23*	−0.23
	[−0.40]	[1.50]	[0.069]	[−1.06]	[1.85]	[−1.38]
N. Older brothers	0.073	0.18*	0.19*	0.20**	−0.11	0.034
	[0.66]	[1.77]	[1.87]	[1.98]	[−1.07]	[0.29]
N. Older sisters	−0.19*	0.14	0.16*	0.11	0.058	−0.060
	[−1.91]	[1.46]	[1.80]	[1.06]	[0.61]	[−0.55]
N. Younger brothers	−0.14	0.081	−0.019	0.086	−0.023	−0.12
	[−1.04]	[0.62]	[−0.15]	[0.63]	[−0.13]	[−0.73]
N. Younger sisters	−0.096	−0.078	−0.16	−0.23	0.19	0.20
	[−0.61]	[−0.49]	[−1.11]	[−1.30]	[0.81]	[0.84]
School attendance	−0.11	0.14	0.18	−0.088	0.29	0.31
	[−0.51]	[0.74]	[0.93]	[−0.38]	[1.59]	[1.28]
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	634	634	634	634	634	627
R-squared	0.85	0.82	0.85	0.80	0.80	0.80

Notes: Robust z-statistics in brackets. Errors are clustered over households. All specifications include a constant term.
***** and * denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.6 Components of wellbeing indicators, full-sample regressions.

Domain	Indicator	Coeff.	*t*-stats	Obs	R^2
Hopeful	Thinks that they are doing very well	−0.30***	[−3.27]	941	0.02
	Thinks of ways to get important things	−0.36***	[−3.63]	941	0.02
	Doing just as well as other children	−0.28***	[−2.97]	940	0.01
	Comes up with many solutions to problems	−0.25***	[−2.81]	941	0.01
	Things done in past will help in future	−0.15*	[−1.70]	939	0.01
	Solves problems when others want to quit	−0.18**	[−2.02]	941	0.01
Emotional wellbeing	Bored	−0.090	[−1.18]	941	0.02
	Has something important to contribute to society	−0.22***	[−2.80]	940	0.03
	Belongs to a community	−0.21**	[−2.58]	940	0.03
	Society is becoming a better place	−0.23***	[−2.93]	940	0.02
	People are good	−0.22***	[−2.72]	938	0.02
	The way society works makes sense	−0.40***	[−5.13]	941	0.02
	Likes own personality	−0.31***	[−3.88]	941	0.02
	Good at managing responsibilities	−0.39***	[−4.38]	939	0.03
	Trusting relationships with other children	−0.39***	[−4.34]	938	0.04
	Experiences that make them become better	−0.27***	[−3.20]	941	0.02
	Confident to express own ideas	−0.19**	[−2.16]	939	0.02
Self-efficacy	Always manage to solve difficult problems	−0.32***	[−3.72]	939	0.02
	Finds means to get what they want when opposed	−0.29***	[−3.37]	941	0.02
	Easy to accomplish goals	−0.25***	[−2.78]	941	0.02
	Confident dealing with unexpected events	−0.19**	[−2.20]	941	0.01
	Knows how to handle unforeseen situations	−0.21**	[−2.41]	941	0.02
	Solves most problems if puts in effort	−0.18**	[−2.09]	939	0.01
	Calm when facing difficulties	−0.18**	[−2.05]	941	0.01
	Finds solutions when confronted with a problem	−0.21**	[−2.40]	940	0.02
	If in trouble, can think of a solution	−0.17*	[−1.86]	940	0.01
	Handle whatever comes their way	−0.22**	[−2.56]	940	0.02

Notes: Robust t-statistics in brackets. Controls include age, gender, school attendance, numbers of older brothers, younger brothers, older sisters, younger sisters, monthly spending and a wealth index. Errors are clustered over households. Each row summarizes results from separate regressions. All specifications include a constant term.

***** and * denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.7 Components of wellbeing indicators, within-household regressions.

Domain	Indicator	Coeff.	*t*-stats	Obs	R^2
Hopeful	Thinks that they are doing very well	−0.023	[−0.084]	107	0.54
	Thinks of ways to get important things	−0.33	[−1.08]	107	0.59
	Doing just as well as other children	−0.34*	[−1.75]	107	0.67
	Comes up with many solutions to problems	−0.059	[−0.21]	107	0.61
	Things done in past will help in future	0.099	[0.32]	107	0.43
	Solves problems when others want to quit	−0.028	[−0.10]	107	0.56
Emotional wellbeing	Bored	−0.0099	[−0.037]	107	0.51
	Has something important to contribute to society	−0.41*	[−1.70]	107	0.41
	Belongs to a community	−0.33	[−1.15]	107	0.44
	Society is becoming a better place	−0.29	[−1.19]	106	0.52
	People are good	−0.32	[−1.39]	107	0.65
	The way society works makes sense	−0.31	[−1.29]	107	0.45
	Likes own personality	−0.086	[−0.42]	107	0.68
	Good at managing responsibilities	−0.44*	[−1.94]	106	0.67
	Trusting relationships with other children	−0.027	[−0.15]	107	0.56
	Experiences that make them become better	−0.23	[−1.01]	107	0.57
	Confident to express own ideas	−0.053	[−0.21]	107	0.55
	Always manage to solve difficult problems	−0.033	[−0.14]	107	0.62
	Finds means to get what they want when opposed	−0.29	[−0.99]	107	0.46
	Easy to accomplish goals	−0.18	[−0.81]	107	0.70
Self-efficacy	Confident dealing with unexpected events	−0.26	[−1.21]	107	0.54
	Knows how to handle unforeseen situations	−0.14	[−0.49]	107	0.56
	Solves most problems if puts in effort	−0.35	[−1.46]	107	0.56
	Calm when facing difficulties	−0.30	[−1.20]	107	0.56
	Finds solutions when confronted with a problem	−0.098	[−0.37]	107	0.42
	If in trouble, can think of a solution	−0.037	[−0.13]	107	0.57
	Handle whatever comes their way	−0.23	[−1.00]	106	0.58

Notes: Robust t-statistics in brackets. Controls include age, gender, school attendance, numbers of older brothers, younger brothers, older sisters, younger sisters, monthly spending and a wealth index. Errors are clustered over households. Each row summarizes results from separate regressions. All specifications include a constant term.

****** and * denote statistical significance at the 10%, 5%, and 1% level, respectively.