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The long shadow of child labour on adolescent mental health: a quantile approach

Danusha Jayawardana[1] · **Nadezhda V. Baryshnikova**[2] · **Terence C. Cheng**[3]

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Abstract
This study examines the heterogeneous effect of child labour on adolescent mental health using longitudinal household data from the Indonesia Family Life Survey. We use legislative minimum wage as an instrument to address the endogeneity bias of child work. Results from the instrumental variable quantile estimation indicate that the effect of child labour is heterogeneous across the mental health distribution. Specifically, working as a child increases the mental health score (CES-D score) at all quantiles and the magnitude of the effect is large above the median of the distribution. This suggests that child workers are likely to develop depression later in life, especially adolescents with poor mental health. Additionally, we find that the effect of child work on adolescent mental health is greater for boys compared to girls.

Keywords Indonesia child labour · Mental health · Instrumental variable · Quantile regression

JEL Classification I14 · I15 · I31 · J82

1 Introduction

Child labour is a global concern. In 2016, 1 in 10 children worldwide engaged in child labour, with the global count totalling 152 million children. Half of these children (73 million) are involved in hazardous work that directly endangers their health and

✉ Danusha Jayawardana
d.jayawardana@uq.edu.au

1 Centre for the Business and Economics of Health, The University of Queensland, St Lucia, QLD 4072, Australia

2 School of Economics, The University of Adelaide, 10 Pulteney Street, South Australia 5005, Australia

3 Department of Global Health and Population, Harvard T.H. Chan School of Public Health, 665 Huntington Ave, Boston MA 02115, United States

safety (ILO 2017). The risk from exposure to dangerous chemicals, or exhaustion due to long hours, can cause physical injuries and morbidities, with some injuries leading to persistent health problems even into adulthood (Edmonds 2007).

It is well documented that child labour adversely affects a child's short- and long-term physical health (Beegle et al. 2009; Guarcello et al. 2004; Kana et al. 2010; O'Donnell et al. 2005; Wolff 2008). Working as a child can also negatively impact psychological well-being, with child labour being identified as a type of childhood adversity (Sturrock and Hodes 2016). Studies from psychology show that being exposed to adverse events in childhood can harm a child's mental well-being, and that the effects can be persistent (Hammen 2005; Kendler et al. 1999). Frequent and prolonged exposure to adversity inevitably leads to toxic stress. This in turn adversely affects the development of the brain leading to mental health disorders such as depression (Franke 2014).

In this study, we examine the heterogeneous effect of child labour on adolescent mental health. We use the Indonesian Family Life Survey (IFLS), which is one of the few longitudinal datasets that collect validated measures of mental health in a developing country setting. We use the 10-item Centre for Epidemiological Studies Depression Scale (CES-D) as the measure of mental health status. To address the issue that the decision to work as a child is potentially endogenous, we employ an instrumental variable strategy based on a quantile approach to estimate the effect of child labour across the mental health distribution.

We make several contributions to the literature on child labour. First, we add to the evidence base on the health effects of child labour, particularly in relation to mental health. While there is a number of studies investigating the effects of child labour on physical health (Beegle et al. 2009; O'Donnell et al. 2005; Sim et al. 2017), few studies have examined mental health. For instance, two recent studies investigate the causal effect of child labour on contemporaneous mental health in India and Vietnam (Feeny et al. 2021; Trinh 2020). Our study differs from these as we focus on the *future* mental health effects of child labour. This is important as the practice is widespread in many developing countries, especially in Indonesia which is the setting of our study, and as a childhood adversity it could lead to persistent mental health effects (Hammen 2005). Understanding the long-term implications of child labour on mental health would guide the design of policies to mitigate the harmful effects on children's overall well-being.

Second, our study differs from the existing studies on child labour in terms of methodology. Following Powell (2020), we apply a Generalised Quantile Regression (GQR) model in an instrumental variable framework to examine whether the effect of child labour varies along the mental health distribution, while addressing the potential endogeneity. In contrast to estimating the average effect, the distributional approach facilitates in understanding the heterogeneous impacts of child work over the adolescent mental health distribution. In particular, it identifies whether working as a child will always have a negative effect on mental health or whether there will be no or even a positive effect on certain adolescents in the mental health distribution.[1]

[1] This is because some children may engage in light work (such as fishing, cattle rearing), as opposed to hazardous work, leading to positive effects on physical health (Kana et al. 2010), and thereby potential spillover effects on mental health. See 2.2 for further discussion.

Our results reveal that child labour overall has a substantial negative impact on a child's adolescent mental health status which is heterogeneous across the mental health distribution. Specifically, working as a child increases the CES-D score at all quantiles, and the effect is strong for adolescents above the median of the distribution. Since a higher CES-D score reflects more pronounced depressive symptoms, this implies that child workers are likely to develop depression later in life, especially adolescents with poor mental health status. Additionally, we find that the effect of child labour on adolescent mental health is greater for boys compared to girls.

The remainder of the paper is structured as follows. Section 2 provides a background to the study. Section 3 describes the data and measures. Section 4 discusses the econometric model followed by empirical results in Sect. 5. Section 6 concludes.

2 Background

2.1 Child labour and mental health in Indonesia

Child labour is defined as children between the ages of 5–14 years old who are economically active (ILO 2002). Nearly ten per cent of children worldwide are in child labour accounting for a total of 152 million (ILO 2017). There is a high prevalence of child labour in Indonesia. In absolute terms, Indonesia consists of 1.7 million child workers, which is the second highest number of child workers in the Southeast Asian region (Aldobrandini and Panisperna 2014).[2] As a percentage, 6.9% of children across Indonesia engaged in child labour in 2009. Alarmingly, close to half of these child workers are involved in hazardous work (BAPPENAS & UNICEF 2017). Consistent with global trends, in Indonesia, boys are more likely to undertake work compared with girls (7.7 vs 6%, respectively). Moreover, child labour is most prominent in rural areas where the prevalence is twice as large compared with urban areas. Sector-wise, the highest number of children aged between 10 and 14 years is employed in the agricultural sector which accounts for 62%, whereas the industrial and services sectors consist of 12% and 26%, respectively (as cited in BILA (2020)).

According to the WHO (2017), 6.4% of individuals aged 15 years and above have mental health disorders in Indonesia. This is likely to be an underestimate as there exists considerable stigma around mental health issues. Sufferers are often stereotyped and discriminated, and as a result are reluctant to seek medical treatment or professional counselling. The prevalence of mental health problems is increasing overtime. Between 1990 and 2006, the estimated number of disability-adjusted life years (DALYs) for depressive disorder increased by 37.5% (Mboi et al. 2018). Mental health disorders are emerging to become one of the major causes of disability in the country (Mboi et al. 2018).

[2] When considering the prevalence of child labour in the Southeast Asian region, Vietnam has the highest number of child workers (2.5 million), followed by Indonesia (1.7 million) and Cambodia (0.5 million).

2.2 Related literature

While there is a plethora of studies examining the effects of child labour on educational outcomes (see Dumas 2012; Emerson et al. 2017; Heady 2003; Gunnarsson et al. 2006; Zabaleta 2011, among others), only a handful of studies examined the long-term health effects of child work (Beegle et al. 2009; Kana et al. 2010; O'Donnell et al. 2005; Wolff 2008). The relationship between child work and health is complex, as it can be either direct or indirect, positive or negative, causal or spurious (O'Donnell 2002). The available empirical evidence is somewhat mixed. Using data from Vietnam, Beegle et al. (2009) do not find any significant effect of child labour on both short- and long-term physical health. O'Donnell et al. (2005), on the other hand, show that while child labour does not have a negative effect on physical health in the short-run, a negative effect is present in the long run particularly for girls. Both studies use the same panel data from Vietnam.

In contrast, Sim et al. (2017) find that child work adversely affects the growth of lung capacity 7 years post-work in Indonesia. Using panel data from the third and fourth waves of IFLS, the study further shows that child work adversely impacts the development of mathematics skills, while there is no effect on cognitive skills and educational attainment. Based on evidence from Cambodia, Kana et al. (2010) argue that working as a child can have a positive effect on physical health if the child works below the threshold level of less than 45 h per week. Child work has positive benefits as many children in rural Cambodia engage in light work such as fishing and cattle rearing which are not harmful for children's physical health.

In addition to physical health, child labour can also affect mental health, as it is identified as a type of childhood adversity (Sturrock and Hodes 2016). This is because frequent and prolonged adverse events in childhood can lead to persistent negative impacts on child's mental well-being (Hammen 2005; Kendler et al. 1999). Two recent studies provide causal evidence on the contemporaneous effects of child labour on mental health. Drawing data from India, Feeny et al. (2021) document a robust negative effect of child labour on the child's psychological well-being. Similarly, a study by Trinh (2020) finds that working as a child has a strong negative effect on current mental health, using data from two developing countries—India and Vietnam, and employing rainfall as an instrument. Moreover, this study also shows that the impact of child labour on mental health is severe for boys compared to girls. Similar to Kana et al. (2010), the study finds that household work which can be classified as light work tends to have a positive effect on mental health.

The existing literature mostly focuses on the average contemporaneous mental health effects of child labour. Therefore, in this study, we examine the distributional effects of child labour on future mental health.

3 Data and measures

We use data from the IFLS, a nationally representative and comprehensive longitudinal survey of families and households in Indonesia. The IFLS sample frame comprises of individuals residing in 13 of the country's 26 provinces which make up 83% of the Indonesian population. There is relatively low attrition, with the re-contact rate of over 85% in each wave (Strauss et al. 2016). There are currently five waves covering years 1993 (IFLS 1), 1997/98 (IFLS 2 and IFLS2+), 2000 (IFLS 3), 2007 (IFLS 4) and 2014 (IFLS 5).

In this study, we use data from the two most recent waves of the IFLS (2007 and 2014) since questions on mental health and childhood adverse events were first included in 2007. The 2007 wave comprises of 8,505 children between the ages of 5–14 years. We track these children over time and estimate the effect of undertaking child labour in 2007 on mental health status after a period of 7 years in 2014. After excluding missing observations in both waves, our sample comprises of 3842 individuals from 3380 households. [3] We highlight that our estimation sample consists of children aged 8–14 years in 2007, since mental health data is only collected for those 15 and above.

3.1 Measure of child labour

Following the ILO definition, we consider child labour as children between the ages of 5–14 years old in 2007 who are economically active. Being economically active would include participation in wage work and unpaid work as part of a family business (Edmonds 2007). Household work or chores are not considered as child labour. In the 2007 wave of the IFLS, information on child labour is collected in a child module administered to children below 15 years of age. We use this information to construct a binary child labour status which takes a value of 1 if the child has engaged in economic work (that is wage work and/or non-paid family work) in the past month and 0 otherwise. The IFLS also collects information on whether the child has *ever* worked for wages or family businesses. We consider this alternative definition of child labour as a robustness check.

3.2 Measure of mental health status

The adult modules of waves 4 (2007) and 5 (2014) of IFLS report data on the 10-item Centre for Epidemiological Studies Depression Scale (CES-D), which we use to construct our measure of mental health. The CES-D is a self-reported measure of depression based on a battery of ten questions (Radloff 1977). As a validated scale, it has consistent performance in both developed and developing countries and is widely used in research (Mackinnon et al. 1998). The ten questions in the CES-D ask how often respondents experienced a set of depressive symptoms during the week prior to the survey. The full list of questions is shown in Table S1 in the supplementary materials.

[3] We dropped a total of 4147 observations due to missing information on mental health in 2014 wave. Of these observations we dropped, 2811 are of individuals who were of ages 5–7 years in 2007 with no information on mental health status in 2014 given that this information is collected from respondents age 15 years and above. This implies that 1336 children aged 8 years and over who appeared in the 2007 survey are missing from the 2014 sample. This is almost 16% of the sample in 2007. The literature finds that attrition does not lead to serious biases, even in the presence of large sample attrition and statistical evidence of attrition bias (Fitzgerald et al. 1998; Jones et al. 2006; Cheng and Trivedi 2015). Nonetheless, we formally check the robustness of our estimates arising from attrition using inverse probability weighting discussed under Sect. 5.4.

Respondents are asked to provide their answers using four possible responses ranging from 0 to 3 (0 = rarely or none of the time; 1 = some or little of the time; 2 = moderately or much of the time; 3 = most or almost all the time). The CES-D score is then calculated by summing across these ten responses, with positively phrased statements reverse-coded. The score ranges from 0 (no depression) to 30 (severe depression), with a higher score reflecting a higher level of depressive symptoms. The Cronbach's alpha is 0.728, which suggests a good level of internal consistency. A CES-D score of 10 or above indicates the presence of clinical depression (Andresen et al. 1994).

3.3 Minimum wage

The decision to work as a child is plausibly endogenous due to simultaneity and omitted variable bias. To address this, we rely on an instrumental variable framework as our identification strategy. Following Sim et al. (2017) we consider provincial minimum wage as a valid instrument in our study context. A detailed discussion on the potential endogeneity of child work and instrumental validity is provided in Sect. 4.1.

The minimum wage data is extracted using both administrative and publicly available data on provincial minimum wage published by the Statistics Indonesia.[4] For child workers, we match the prevailing minimum wage in the year and province in which the individual began working. [5] For non-child workers, we follow the approach in Sim et al. (2017), using the predicted year that these non-workers would have started work. The approach involves estimating a regression of the starting year on birth year using the sample of child workers, and thereafter using the estimated coefficients to predict the starting year for non-workers. Table S4 in the supplementary materials presents the average minimum wage for each province derived using the above approach.

3.4 Covariates

Mental health depends on variety of factors including gender, age and economic circumstances (WHO 2017). In our analysis, we account for these effects by controlling for an extensive set of characteristics describing the respondents in our sample. These characteristics are broadly classified as demographic and socioeconomic factors, past experience with adverse events, religiosity and social capital, health status, and habits and behavioural factors. Below, we discuss the covariates used in the analysis in detail. We highlight that apart from child labour status, proxies for past income and crime which are observed in 2007, all other covariates are observed in 2014. A full description of these variables is given in Table S5 in the supplementary materials.

Demographic and socioeconomic factors include respondents' gender, age, marital status and employment status. Poverty has been shown to be an important determinant

[4] This is available at https://www.bps.go.id/linkTableDinamis/view/id/917. Accessed on 10 November 2021.

[5] We derive this based on the survey question 'At what age did the child start working?' In our sample, the average age at which children started to work is 9.6 years (see Table S2 for the distribution of the age at which children started to work based on data from IFLS 4 (2007) wave). However, as presented in S3, there are some differences in the age that children started working across provinces, though it does not vary by urban/rural area.

of mental health (Currie 2009; Tampubolon and Hanandita 2014). To capture the extent of poverty, we include the monthly household per capita food and non-food expenditure as a proxy for economic status. We further account for dwelling conditions such as whether the household uses nearby river, land or sea as the toilet, and whether the household uses firewood for cooking. To capture temporal persistence in the effects of poverty, we include the measures of monthly per capita expenditure and dwelling conditions from the 2007 survey wave in our estimation.

Experience of adverse events increases the risk of depression. Studies from psychology have shown that stressful or adverse events experienced as a child can have a negative impact on mental health as an adult (Fryers and Brugha 2013; Hammen 2005). The 2014 survey includes a battery of questions that allows us to identify whether respondents were exposed to adversity during their childhood. These include whether they have experienced hunger, and whether they have been confined to bed or home for a month or more because of a health condition, in their childhood. We also include variables that describe adverse parental characteristics in childhood such as whether their parents used to smoke or drink heavily, had poor mental health problems and were no longer married. We further account for whether individuals have experienced stressful life events such as accidents, natural disasters and economic disruptions collected in the 2014 survey, and have been a victim of crime (2007 survey).

Religiosity has been shown to reduce psychological distress and lead to better mental health status (Koenig et al. 2012). We account for religiosity using an indicator variable of whether the individual reported to be very religious or somewhat religious. We also include two proxies for social capital—individuals' willingness to help and participation in community activities. Social capital, which refers to the network of relationships, has been shown to be inversely associated with mental disorders (Johnson et al. 2017; Tampubolon 2012).

Mental health also depends on physical health status (Liew 2012), and to account for it, we include the self-reported health status. We further account for behavioural risk factors such as smoking, consumption of fruits and vegetables, consumption of soft drinks and physical activities. These habits have been (Liew and Gardner 2016; Mujcic and Oswald 2016; Ocean et al. 2019; Rebar et al. 2015). As an anthropometric measure, we include dummy variables which identify whether the individual is underweight, overweight or obese, based on body mass index (BMI) (Peltzer and Pengpid 2018). We use the BMI criterion for Asian adults proposed by the WHO (2000) for classification purposes.

Finally, we include geographical controls of urban or rural residence and province identifiers to control for the regional heterogeneity.

3.5 Descriptive statistics

The summary statistics describing our sample are shown in Table S6 in the supplementary materials. Eight per cent of respondents have engaged in child labour. They have significantly higher average depressive symptom score compared with those who did not work as children (8.08 vs 7.41, $p < 0.01$). Figure 1 shows the distribution of the CES-D score by child work status, which clearly indicates that child workers

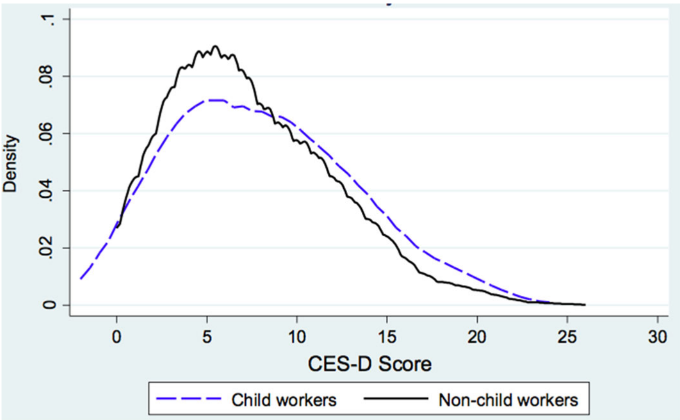

Fig. 1 Distribution of mental health score of child workers and non-child workers. *Notes*: This figure is based on data from IFLS 4 (2007) and IFLS 5 (2014) waves. Higher CES-D score reflects more pronounced depressive symptoms

have a distribution of scores that are skewed slightly to the right. Half of our sample respondents are girls, and the average age of our sample is 17.6 years. The majority of respondents live in an urban area (64%) and are still attending school (54%). Child workers differ significantly from non-workers in a number of attributes. For example, 42% of respondents who were child workers are currently employed whereas among non-workers this percentage is 23%. Child workers are also less likely to be in school (33 vs 56%). Furthermore, child workers are from poorer households with lower household expenditures and are more likely to report poverty-related characteristics.

The effect of child labour on mental health at an early age (for example, at 7 years) might be different than experiencing it at an age closer to the school leaving age (for example, at 14 years). Figure S1 in the supplementary materials depicts the heterogeneity of child labour by age. As anticipated, labour market participation increases at an increasing rate with age. Specifically, we observe that the incidence of child labour among children below 10 years is around 5%, whereas almost 20% of children aged 14 years are child workers. This suggests that older children are more likely to engage in labour market activities.

4 Econometric model

Identification of the causal effect of child labour on adolescent mental health is challenging as a number of circumstances would potentially result in endogeneity problems. First, endogeneity can arise from simultaneity, or a bi-directional relationship between the likelihood of working as a child and health status. Specifically, on one hand, child labour would result in deterioration of health, as children are more vulnerable to hazardous and stressful working conditions (Fassa 2003). On the other hand, the health condition of the child would influence whether the child is capable of working. Healthier children—both physically and mentally—are likely to be more productive and have higher propensity for engaging in work, which is referred to as 'healthy worker selection effect' (O'Donnell et al. 2005). The former suggests a negative relationship between child work and health, whereas the latter suggests a positive relationship.

Second, omitted variables such as preferences and attitudes of parents can influence child's decision to work and health status. O'Donnell et al. (2005) assert that a 'preference effect' can arise because of such unobserved heterogeneity. For example, parents who are more concerned about the well-being of their children may be less likely to allow them to undertake any type of work. These parents may also be likely to allocate more resources to improve the child's health. Taken together, the preference effect suggests that child health and work status are negatively related (O'Donnell et al. 2005).

4.1 Identification strategy

The presence of endogeneity may result in biased estimates. We address the potential endogeneity problem using an instrumental variable (IV) quantile regression model. Previous studies examining the effects of child labour on health have used a variety of instruments such as price of rice (Beegle et al. 2009; O'Donnell et al. 2005), household land-holdings (Kana et al. 2010; O'Donnell et al. 2005), school quality (O'Donnell et al. 2005; Wolff 2008), migrant ratio (O'Donnell et al. 2005), dependency ratio (Kana et al. 2010), local adult employment rate (Wolff 2008), rainfall (Trinh 2020) and minimum wage (Sim et al. 2017).

The validity of an instrument depends on its relevance and excludability. In our application, instruments such as the price of rice, household landholdings, school quality, migrant ratio, dependency ratio are not valid instruments due to potential violation of the exclusion restriction. Moreover, rainfall could also possibly violate the exclusion restriction, causing doubt on its validity, especially in the context of Indonesia. For instance, if there are natural disasters such as floods caused by heavy rainfall, then this could have a direct effect on mental health. Baryshnikova and Pham (2019) show that natural disasters, in fact, lead to lower mental health. Further, given that Indonesia is more prone to natural disasters it is likely that there could be large deviations in rainfall and thus would not be an appropriate instrument in our study context.[6] Therefore, we consider minimum wage proposed by Sim et al. (2017).

According to Sim et al. (2017), adult minimum wage affects the supply of child labour. Since child labour stems from economic vulnerabilities and poverty (Basu and Van 1998), a higher minimum wage would lower child labour through improved income and living conditions. On the contrary, a rise in the minimum wage could also lead to an increase in the supply of child work if such wage increase causes adult unemployment to rise. This is especially true in the context of less developed countries where unemployment benefits are often non-existent, which compels unemployed parents to send their children to work (Basu 2000). Based on the above arguments minimum wage is likely to satisfy the instrument relevance criteria.

[6] We have explored the feasibility of using rainfall as an instrument to determine the effect of child labour on mental health. When doing so the econometric estimates we obtained were of the wrong sign, which suggests a potential violation of the exclusion restrictions.

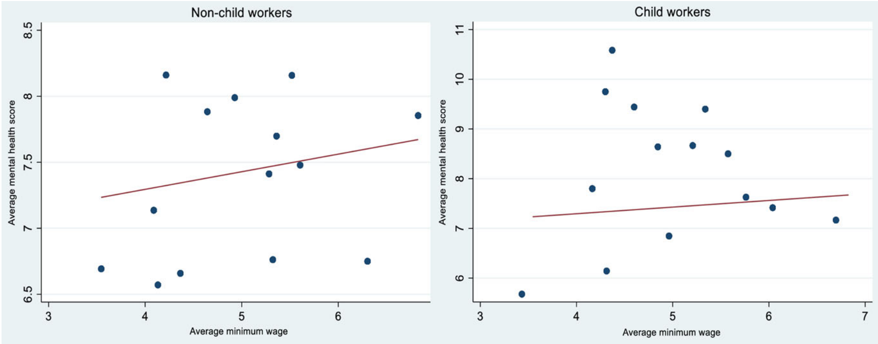

Fig. 2 Plot of average mental health score and minimum wage. *Notes*: The mental health score is derived using the CES-D-10 index. Minimum wage is expressed in hundreds of thousand rupiahs

Unlike relevance, whether the minimum wage satisfies the exclusion restriction is not straightforward. Sim et al. (2017) argue that the process by which the minimum wage is calculated in Indonesia satisfies the excludability criteria. Indonesian minimum wage is determined using a basket of consumption goods required to cover the basic needs of a single worker (Suryahadi et al. 2003). Such a determination implies that the minimum wage level is based on province-specific conditions rather than individual-specific conditions. Furthermore, differences between provincial minimum wages capture fluctuations in prices and the level of bargaining in each province (Sim et al. 2017), and thus, it is unlikely that minimum wage will have a direct effect on mental health status. We discuss further sources of potential violation of the exclusion restriction in the robustness checks.

To highlight that the minimum wage does not have a direct effect on mental health, we derive a plot of average mental health of child workers and non-child workers in each province in 2014 against the average minimum wage for individuals from that province in 2007. Figure 2 shows that there is no significant pattern implying no correlation between minimum wage and mental health.

4.2 Estimation equation

Our econometric specification is motivated by the theoretical framework proposed by Kana et al. (2010). Building on the household utility maximisation theory and the work of Rosenzweig and Schultz (1983), it is shown that child human capital including child education and health, depends on the amount of time the child allocates for schooling, work and leisure, among other variables (see Kana et al. 2010). Based on this argument, we formulate the below classical two-stage model to estimate the effect of child work on adolescent mental health.

$$MH_{i,2014} = \alpha + \beta CL_{i,2007} + \eta \mathbf{X}'_{i,2014} + \varphi \mathbf{P}'_{i,2007} + \varphi_i + \varepsilon_i \tag{1}$$

and

$$CL_{i,2007} = \gamma + \delta \mathbf{MinWage}_{it} + \psi \mathbf{X}^{'}_{i,2014} + \vartheta \mathbf{P}^{'}_{i,2007} + \varphi_i + \upsilon_i \tag{2}$$

where Eqs. (1) and (2) are the structural and first stage equations, respectively. $MH_{i,2014}$ is the mental health score based on CES-D scale for the ith individual in 2014. Our main independent variable is $CL_{i,2007}$, an indicator variable that equals to one if the individual has worked as a child in 2007 and zero otherwise. $\mathbf{X}_{i,2014}$ is a vector of covariates representing socio-demographics, childhood adversity, religiosity, social capital, health status, habits and behavioural factors of individual i in 2014.

$\mathbf{P}^{'}_{i,2007}$ is the vector of covariates denoting proxies of income and crime experience of individual i in 2007. φ_i denotes the provincial fixed effects based on respondent's residential status in 2014 and ε_i is the error term. The instrumental variable of $MinWage_{i,t}$ represents the minimum wage in the year t and province in which the individual i began working. This suggests that our IV is essentially an interaction between these two variables. Given that we control for provincial fixed effects, the identification stems from within provincial variation and variation in the age that the respondent started to work.

The generalised quantile approach of Eq. (1) is:

$$\begin{aligned} Q_{MH_{i\ 2014}}\left(\tau_j | CL_{i\ 2007}, X_{i\ 2014}, P_{i\ 2007}\right) = \alpha\left(\tau_j\right) + \beta\left(\tau_j\right) CL_{i\ 2007} + \eta(\boldsymbol{\o}_{\mathbf{j}}) \mathbf{X}^{'}_{i\ 2014} \\ + \varphi(\boldsymbol{\o}_{\mathbf{j}}) \mathbf{P}^{'}_{i\ 2007} + \varphi_i\left(\tau_j\right) + \varepsilon_i\left(\tau_j\right) \end{aligned}$$

for all quantiles $\tau_j \in (0, 1)$. The effect of child labour on individual i in year 2014 is given by $\beta(\tau_j)$, while $\eta(\tau_j)$ and $\varphi(\tau_j)$ capture the effects of a change in other controls on the CES-D score as functions of quantiles.

We apply the generalised quantile regression (GQR) method proposed by Powell (2020) to estimate the above equation. The advantage of GQR method over other traditional quantile estimators is its flexibility in deriving unconditional quantile treatment effects (QTE) even after conditioning for other additional covariates (Powell 2020). An exception to this is the instrumental-variable estimator for unconditional QTEs developed by Frölich and Melly (2013). However, this method only identifies the QTEs for the group of compliers and requires a binary instrument. In contrast, GQR estimator is developed in a general instrumental variable framework which distinguishes between treatment and control variables and does not impose a local quantile treatment effect (LQTE) condition (Powell 2020). Further, the GQR method of Powell (2020) permits both discrete and continuous instruments, providing us with an ideal estimator to address the endogeneity of child labour using the proposed instrumental variable (minimum wage) and thereby to identify the unconditional QTEs.

5 Empirical results and discussion

5.1 The heterogeneous effect of child work on mental health

Table 1 presents the estimated effects of child work on mental health. We show estimates from two generalised quantile regression models—without and with instrumental variable.[7] As anticipated both models depict that the effect of child labour on mental health score is positive and heterogeneous throughout the entire distribution. As discussed above, given the concerns of endogeneity, we focus on the estimates from the instrumental variable quantile regression (see Panel B). Accordingly, we observe that this effect is statistically significant at 1% level for 0.5 quantile and above. The largest effect is on the 0.75 quantile which shows that undertaking work as a child increases the CES-D score by 0.9 points (Panel B, Column 3). Similarly, to those individuals in the median (0.5 quantile) and the 0.9 quantile of the distribution, working as a child increases the mental health score approximately by 0.5 and 0.3 points, respectively. A CES-D score greater than 10 implies clinical depression, and we observe that this range lies above the 0.5 quantile of the mental health distribution.[8] Therefore, these results imply that child workers are at a high risk of developing depression later in life.

Considering the sample average mental health score of 7.5, the estimated effects translate to 4.5–12% (i.e. 0.07–0.19 standard deviations) increase in mental health score. Interestingly, the magnitudes of these effects are similar to that of physical health effects of child work in Indonesia. For instance, Sim et al. (2017) find that on average, compared to non-child workers, child workers have 0.38 standard deviations lower growth in the lung capacity over a 7-year period leading to poor respiratory health. According to Wolff (2008), child workers have a 15% higher probability of suffering from complaints related to physical health in the contemporaneous period.[9]

It is important to note that our results present the combined effect of work outside family (wages) and work within family business (either farm or non-farm). This is to ensure a sufficient sample size for quantile regressions. Specifically, out of our total sample of child workers (312), only 40 individuals (13%) have worked for wages while the remaining have worked for family business (274 individuals).[10] Further, we believe that splitting the sample into wage work and family work can be endogenous due to potential selection bias. This is because both physically and mentally healthy children are more likely to engage in work outside family, since such work tends to be more hazardous and strenuous than family work. According to O'Donnell et al. (2005) such 'healthy worker selection effect' can induce a positive relationship between work status and child health. Nevertheless, as a robustness check, we examine whether the effect varies on the type of work by estimating the quantile effects of child work for family business (i.e. we drop those who have worked for wage work). We observe that the magnitudes of the effects are quite similar to the combined effect reported in Panel

[7] We use the STATA command of 'genqreg: Generalised Quantile Regression' written by Baker M, Powell D and Smith T.

[8] See Table S8 for the mental health distribution.

[9] The 2SLS estimate (mean outcome) indicates that working as a child increases the adolescent CES-D score by approximately 5.6 points ($p < 0.1$). This is quite large compared to our reported quantile estimates. However, it is important to note that the 2SLS coefficient is not directly comparable to QTEs due to differences in the estimation methods. Specifically, the quantile estimates denote 'unconditional' QTEs, whereas the 2SLS estimates are 'conditional' effects.

[10] Two individuals have worked for both wages and family business.

Table 1 The effect of child labour on mental health

	0.25 Quantile	0.50 Quantile	0.75 Quantile	0.90 Quantile
Panel A—without IV				
Child work	0.008	0.602	0.807**	0.148
	(0.258)	(0.407)	(0.411)	(0.362)
Observations	3842	3842	3842	3842
Panel B—with IV				
Child work	0.035	0.544***	0.874***	0.332***
	(0.048)	(0.044)	(0.080)	(0.044)
Observations	3842	3842	3842	3842

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis, clustered at individual level using the Markov Chain Carlo algorithm (MCMC). All regressions include the full set of control variables denoting demographics, income proxies, adverse and stressful events, religiosity and social capital, physical health status habits and behavioural factors and provincial fixed effects as given in Supplementary Table S2

B of Table 1. This is expected as 87% of the child workers in our sample are engaged in family work.[11]

The reliability of the instrumental variable estimates reported in Table 1 hinges on the validity of the selected instrumental variable of minimum wage. Given that there is no specific diagnostic test to assess the validity of the instrument in a quantile regression framework, we assess its validity using a linear IV regression model.[12] In this regard, we apply the weak-instrument test proposed by Olea and Pflueger (2013). We find that the effective F statistic is 38.9, which is greater than the critical values indicating that the instrument is not weak.[13]

Inclusion of a large number of covariates can result in 'bad controls' leading to endogeneity bias. Therefore, we test the sensitivity of our results by changing the set of control variables included in our model. In this regard, we estimate three specifications in which we exclude different sets of covariates. Table S9 reports the results from the quantile instrumental variable regression models. In Panel A, we exclude all the control variables except the demographic covariates. It is evident that the coefficient of child work is higher across all the quantiles of the mental health distribution compared to our original specification in Panel D. Panel B includes income proxies but not childhood adversity, habits or behaviour controls. This is because factors such as whether the child has experienced hunger or their health status during childhood can be highly correlated with working as a child and might lead to endogeneity. However, Panel B shows that the exclusion of those does not affect our results. In Panel C, we exclude only habits and behaviour controls due to the same concern of endogeneity. Nevertheless, our results are robust and similar to that of the original specification in Panel D. As

[11] The results are available upon request.

[12] According to Chernozhukov and Hansen (2006), if minimum wage (instrument) induces variation in child labour exogenously (the treatment) and affects the outcome of interest (mental health) only through child labour, it is possible to estimate the causal effect of child labour on mental health over its whole distribution.

[13] The reported critical values for tau = 5%, 10%, 20% and 30% are 37.418, 23.109, 15.062 and 12.039, respectively.

Table 2 Gender heterogeneity

	0.25 Quantile	0.50 Quantile	0.75 Quantile	0.90 Quantile
Panel A—boys				
Child work	−0.528***	1.023***	1.143***	0.976***
	(0.151)	(0.157)	(0.073)	(0.029)
Observations	1890	1890	1890	1890
Panel B—girls				
Child work	0.040	0.584***	0.108*	−0.170***
	(0.055)	(0.118)	(0.064)	(0.034)
Observations	1952	1952	1952	1952

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis, clustered at individual level using the Markov Chain Carlo algorithm (MCMC). All regressions include the full set of control variables denoting demographics, income proxies, adverse and stressful events, religiosity and social capital, physical health status habits and behavioural factors and provincial fixed effects as given in Supplementary Table S2

discussed in Sect. 3.4, all the considered controls can influence child labour as well as mental health. Therefore, to minimise omitted variable bias, we consider the original (full) specification as our preferred specification.

5.2 Gender heterogeneity

The effect of child work on mental health can vary based on gender differences. To investigate this we perform a heterogeneity analysis considering two separate sub-samples of girls and boys. Panels A and B of Table 2 present the quantile estimates for boys and girls, respectively.

Similar to results reported in Table 1, the effect of child work is heterogeneous for both boys and girls. However, compared to girls, boys have a larger effect throughout the entire distribution. This may be due to differences in the nature of work performed by boys and girls. In general, girls are nearly 30% less likely to participate in paid market work, as they are mainly engaged in household chores (Edmonds 2007). We also observe that the effect of child work on mental health is negative for girls at the 0.9 quantile suggesting that working as a child improves mental health for girls who have a higher risk of developing depressive symptoms. Interestingly, our results are consistent with Trinh (2020). Drawing evidence from India, this study also finds that on average child labour has a severe impact on the mental health of boys, while a positive impact on girls emotional health in the contemporaneous period.

5.3 Long-term effect of child work on mental health

Our empirical results show that child workers are likely to have a higher mental health score (i.e. poor mental health) 7 years later. Considering child work status in 2000 (IFLS 3), linked to mental health data in 2014, we now examine whether the effect would still hold after 14 years. Table 3 presents the quantile estimates using the same

Table 3 Long-term effect of child labour on mental health

	0.25 Quantile	0.50 Quantile	0.75 Quantile	0.90 Quantile
Child work (2000)	0.176*	0.200	0.227	0.201***
	(0.097)	(0.167)	(0.177)	(0.047)
Observations	3061	3061	3061	3061

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis, clustered at individual level using the Markov Chain Carlo algorithm (MCMC). All regressions include the full set of control variables denoting demographics, income proxies for 2000 and 2014, adverse and stressful events, religiosity and social capital, physical health status habits and behavioural factors and provincial fixed effects

instrument of minimum wage for child labour in 2000.[14] The effect of child work on long-term mental health is statistically significant at 5% level only at the 0.9 quantile. Compared to estimates reported in Table 1, we further find that the magnitude of the effects is lower for the 0.5 quantile and above. This is plausible given that we estimate the effects after 14 years. Specifically, working as a child increases the mental health score by approximately 0.2 points at the 90th quantile 14 years later. Overall, these results suggest that child labour can lead to long-term impacts, especially for children with poor mental health.

5.4 Robustness checks

The empirical results reported in Sect. 5.1 are based on whether the child has engaged in any economic work (that is wage work and/or non-paid family work) in the past month. In addition to past month labour participation, IFLS also reports information on whether the child has 'ever' engaged in any economic activity. As the first robustness check, we consider this alternative definition of ever worked as the main variable of interest. That is, we assign a value of 1 if the child has ever worked and 0 otherwise. Table 4 presents quantile treatment effects. The results are similar to those reported in Sect. 5.1, indicating that the effect of child work on mental health is robust to the choice of child labour definition.[15]

Second, we check the sensitivity of our estimates to potential attrition bias by using inverse probability weighting (IPW). The IPW estimator solves the attrition issue

[14] According to the weak IV test, the effective F statistic is 48.08, suggesting that the minimum wage is a strong IV for child labour in 2000 as well.

[15] Prior studies that have examined the quantile effects on mental health, have largely found strong effects for individuals with poor mental health (Baryshnikova and Pham 2019; Ohrnberger et al. 2020; Schiele and Schmitz 2016; Stillman et al. 2009; Wright et al. 2021). These effects are generally observed for events that have both negative and positive impacts on mental health. In contrast, we find that the quantile effect of child labour is higher around the median (0.5 and 0.75) compared to the top of the mental health distribution (0.9). This is because the results from the pooled analyses mask heterogeneity in the effects by gender across the different quantiles. Specifically, the effect of child work on mental health is negative for girls at the 0.9 quantile, suggesting that working as a child improves mental health for girls who have a higher risk of developing depressive symptoms. Our results are consistent with Trinh (2020), which reports that on average child labour has a positive impact on girls' emotional health. This is plausible given that girls tend to engage in light work (Edmonds 2007) which can lead to positive effects on mental health (Kana et al. 2010).

Table 4 Robustness check: the effect of child work on mental health—alternative definition

	0.25 Quantile	0.50 Quantile	0.75 Quantile	0.90 Quantile
Child work (ever)	−0.045*	0.570***	0.805***	0.344***
	(0.027)	(0.088)	(0.019)	(0.027)
Observations	3842	3842	3842	3842

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis, clustered at individual level using the Markov Chain Carlo algorithm (MCMC). All regressions include the full set of control variables denoting demographics, income proxies, adverse and stressful events, religiosity and social capital, physical health status habits and behavioural factors and provincial fixed effects as given in Supplementary Table S2

Table 5 Robustness check: effect of child labour on mental health using inverse probability weighting (IPW)

	0.25 Quantile	0.50 Quantile	0.75 Quantile	0.90 Quantile
Child work	0.104*	0.546***	0.668***	0.557***
	(0.056)	(0.125)	(0.113)	(0.009)
Observations	3842	3842	3842	3842

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parenthesis, clustered at individual level using the Markov Chain Carlo algorithm (MCMC). All regressions include the full set of control variables denoting demographics, income proxies, adverse and stressful events, religiosity and social capital, physical health status habits and behavioural factors and provincial fixed effects as given in Supplementary Table S2

assuming that the data are missing at random, that is conditional on the observables there is no systematic correlation between the probability of response and the outcome of interest (mental health score). To calculate the weights, we first estimate the probability of responding to the two waves of the survey as a function of the respondents' observed characteristics in the 2007 wave (Wooldridge 2010). Next, we obtain the inverse of the fitted probabilities of the response function. Finally, these weights are used to adjust the estimates from the instrumental variable quantile regressions. The attrition adjusted estimates are shown in Table 5. Comparing these estimates to the baseline estimates without IPW (Table 1), we observe that the magnitude of the estimated effects is very similar for lower quantiles; at higher quantiles, we observe small differences in the size of the estimates. Overall, these results indicate that our estimates are not significantly affected by sample attrition bias.

Third, we consider the sensitivity of our results to two potential sources of violation of exclusion restriction of the instrument variable. The excludability may be violated due to the intergenerational transmission of mental health within families. Specifically, children's mental health is affected by other family members' mental health, particularly father's (Chi et al. 2019; Powdthavee and Vignoles 2008). Given that minimum wage changes can affect parental mental health, not accounting for it can lead to a correlation between the error term and the instrument. To address this potential endogeneity, we use parental mental health in 2007 (i.e. contemporaneous to child work) as a control variable and show that the results are qualitatively similar (see Table S10 in the supplementary materials).[16]

Another avenue of potential violation of the exclusion restriction can occur if the implementation of minimum wage is a policy choice that is related to the local economic and policy environment. Such environmental factors could possibly be correlated with the economic and labour market conditions faced by the households at the time. This, in turn, may have an impact on the mental health of household members, such as through unemployment and financial stress. To rule out this possibility, we regress household employment and health outcomes in 2007 on minimum wage and observe that the minimum wage does not have an independent effect on employment and health.[17] This provides suggestive evidence that minimum wage is unlikely to affect the mental health of household members through unemployment and financial stress.

5.5 Potential mechanisms

Our results show that child labour has a negative impact on mental health. The effect is significant in all quantiles except the bottom, suggesting that child workers are more likely to have a higher mental health score 7 years later. These results hold even after addressing the endogeneity bias of child work as well as controlling for a wide range of socio-demographic, childhood adversity, health status, habits and behavioural covariates. Therefore, it is important to discuss some potential underlying mechanisms through which this might occur.

Relative to adult work, child workers experience higher health risks since they generally work in small scale, informal and illegal settings which are difficult to regulate (Fassa 2003). In the context of Indonesia, child labour is mostly used in the industries of footwear (sandals), gold, palm oil, rubber, tin and tobacco (as cited in BILA (2020)). These industries are characterised with hazardous working conditions, where child workers are constantly exposed to toxic chemicals (such as nicotine), sharp tools and equipment, long hours of work to meet the required production quota and extreme heat. The statistics show that close to half of total child workers aged 5 to 14 years work in such hazardous conditions (BAPPENAS & UNICEF 2017). Due to physiological and psychological immaturity of children, these conditions would make them more susceptible to abuse and health risks (Guarcello et al. 2004) than adults. In fact, such health risks could persist into adulthood. Specifically, given that childhood is a vulnerable period in brain development (Alwin and Krosnick 1991), the psychological stress and trauma that the child workers experience can have a profound effect on their adolescent mental health. Our study provides evidence to this, as child labour increases the risk of depressive symptoms later in life substantially.

We further examine the gender heterogeneity of the effect of child work on adolescent mental health. Interestingly, we find that in contrast to boys, girls' mental health

[16] Parent's mental health in 2007 is a missing variable for almost 32% of the individuals in our sample, hence it was not considered as a control variable in our baseline model. The results presented in Table S10 are estimated using the dummy variable adjustment for missing values to preserve sample size.

[17] The results are available upon request.

at the top quantile improves by child work. This is plausible considering the nature of the work performed by boys and girls. Girls are more likely to engage in household work (Edmonds 2007), which tends to be light work as opposed to hazardous work. In line with previous studies, engaging in light work can have positive effects on mental health (Kana et al. 2010; Trinh 2020).

6 Conclusion

Child labour constitutes a violation of the fundamental rights of children, while leading to adverse consequences on their wellbeing. The impacts of child labour may extend beyond contemporaneous effects as it can also influence adult health. Particularly, it is shown that certain physical and mental health problems occurred due to working as a child can persist into adulthood. Though there is a limited number of studies on the effect of child labour on physical health—both short and long term, there is no econometric analysis on the heterogeneous impact of child labour on mental health. This paper addresses this empirical gap by examining the causal effect of working as a child across the mental health distribution of adolescents. To this end, we use longitudinal data from the IFLS and employ minimum wage as an instrumental variable to address the endogeneity bias of child work.

The results from the instrumental variable quantile model reveal that child labour overall has a substantial negative impact on a child's adolescent mental health status which is heterogeneous across the mental health distribution. Specifically, working as a child increases the mental health score at all quantiles and the effect is strong above the median of the distribution. This suggests that child workers are likely to develop depression later in life, especially adolescents with poor mental health status.

Our study has several limitations. First, the validity of the IV results depends on the exclusion restriction assumption. That is the minimum wage is strongly correlated with the supply of child work but has no direct effect on mental health status, which we cannot directly test. However, based on the mechanism by which minimum wage is determined in Indonesia, Sim et al. (2017) argue that minimum wage is likely to satisfy the exclusion restriction and, thus, is a valid instrument for child labour especially in the context of Indonesia. Second, the child labour variable only captures whether the child has worked or not and, hence, does not provide comprehensive data on the number of hours worked or the nature of work activity. Both the intensity and type of child work can have different mental health consequences, and therefore is a potential avenue for future research.[18]

Despite limitations, our findings provide novel evidence on the effect of child labour on adolescent mental health. Policy-wise, this study underscores the importance of

[18] The child module of IFLS does contain data on the number of hours worked by child workers, which can be used as a measure of intensity of work. Unfortunately, the minimum wage is not a valid instrument for the number of hours worked (intensive margin), although it is a strong IV for participation in labour market activities (extensive margin).

policy interventions towards eradicating child labour in developing countries as it can lead to adverse long-term mental health effects.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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