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CHILD WELLBEING AND ECONOMIC DEVELOPMENT: EVIDENCE FROM INDONESIA

a thesis

by

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for the degree of
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Abstract

Ensuring a high quality of life for all children is essential for the future human and social capital as well as for sustainable economic growth and development. Hence, child wellbeing has gained much attention in recent years and has also been the ultimate focus of the Sustainable Development Goals. In this context, this thesis primarily focuses on the mental and emotional wellbeing of children, an important but often overlooked aspect of overall child wellbeing. Specifically, the thesis investigates whether harmful practices such as child labour and child marriage can have an impact on children's mental health, issues that remain largely unexplored in the current economics literature. Additionally, the thesis provides empirical evidence on the effectiveness of a social protection program in addressing such issues and ensuring child wellbeing.

The thesis consists of three main chapters that examine three questions on child wellbeing, using longitudinal household data from the Indonesia Family Life Survey (IFLS). First, the thesis examines the impact of early marriage on the mental health of girls in Indonesia. Employing several identification strategies such as fixed effects, coarsened exact matching (CEM) combined with difference-in-differences and instrumental variable approach, this chapter seeks to assess the causal effect between an early marriage of a woman and her mental health status later in life. The results reveal that early marriage has a significant effect on women's mental health status. More specifically, women who marry early (i.e. by the age of 18 years) are more likely to be depressed as well as affected by severe depressive symptoms. Additionally, it is also found that a one-year delay in marriage decreases the probability of having severe depression. These findings are robust to a variety of sensitivity checks.

Second, the thesis investigates the long-term effect of child labour on adolescent mental health. To address the potential endogeneity bias of child work, two instruments - minimum wage and the number of family-owned businesses by the household are employed. Considering the nature of the main outcome variable of interest – the mental health score, this study applies an IV-Poisson model to estimate the effect of child work on mental health. The results reveal that child labour has a substantial negative impact on a child's long-term mental health status. Moreover, we find heterogeneity in the effect of child labour where working as a child for wages increases the mental health score, leading to depressive symptoms. On the contrary, there is no significant impact of working as a child in family enterprises on adolescent mental health. This study further shows that religiosity and social capital can play a role in mediating the adverse long-term effects of child labour on mental health.

Finally, the thesis evaluates the impact of one of the largest subsidised food programs known as 'Raskin' (or rice for the poor) in Indonesia on the labour supply and schooling of children. The main identification issue arises from selection bias due to non-random distribution of the subsidy and unobserved heterogeneity. To address this, coarsened exact matching (CEM) with the difference-in-differences (DD) estimator is implemented. Given that engaging in labour market activities and attending school is a joint decision competing for the child's time, the study uses a bivariate probit model with a matched double-difference approach to estimate the effect of Raskin on the likelihood of child labour supply and school attendance. The results reveal that the subsidised rice program in Indonesia is effective in decreasing the probability of working for boys though there is no impact on the outcomes of girls. Specifically, it is found that the Raskin program significantly reduces the likelihood of working for boys who engage in both working and schooling. These findings provide an important policy implication on how social protection tools can indirectly influence the wellbeing of children.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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DANUSHA GUNASEELA JAYAWARDANA

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Dedication

To my beloved parents, Karu and Dhammika Jayawardana.

Chapter 1

Introduction

1.1 Background

Childhood is an essential period for the development of any human being. Therefore, ensuring a high quality of life for all children is pivotal to allow them to reach their potential and for the realisation of their rights. The empirical evidence shows that providing children with a conducive and supportive environment to grow not only benefits the individual but also the society at large. Hence, child wellbeing has gained much attention in recent years and has also been the ultimate focus of the Sustainable Development Goals (Marguerit et al., 2018).

From an economic perspective, the wellbeing of children is essential for the development of necessary capabilities (Contri & Heckman, 2014) as well as equitable and inclusive societies (UNICEF, 2012) which in turn becomes the foundation for sustainable economic growth and development of a country (Boyden & Dercon, 2012). Besides, investing in children has an impact on the utility of households and contributes to the future human and social capital of a country (Conti & Heckman, 2014; Chapple & Richardson, 2009).

There is no single universally accepted definition for child wellbeing as different institutions have developed various frameworks and indices to measure it. In contrast to terms such as 'welfare' and 'happiness', the concept of 'wellbeing' takes a more holistic approach (Hanafin et al., 2007) to the total quality of life of children (Chapple & Richardson, 2009). Hence, child wellbeing is measured using various dimensions such as material wellbeing, education, health and safety, family and social relationships (Contri & Heckman, 2014; Chapple & Richardson, 2009; UNICEF, 2012).

In this broad setting, this thesis primarily focuses on the mental and emotional wellbeing of children, an important but often overlooked aspect of overall child wellbeing. More specifically, the thesis investigates whether harmful practices such as child labour and child marriage can have an impact on children's mental health, issues that remain largely unexplored in the current economics literature. Additionally, this thesis provides empirical evidence on the effectiveness of a social protection program in addressing such issues and ensuring child wellbeing.

1.2 Research Questions

Despite ongoing policy initiatives, child labour and child marriage remain a widespread concern, especially in the developing countries. According to the International Labour Organisation, 152 million children aged 5 to 17 years are in child labour globally, accounting for almost one in every ten children worldwide. Nearly half of these children (73 million) are in hazardous work that directly endangers their health and safety (ILO, 2017). When considering the issue of child marriage, 1 in 5 women (21 per cent) are married before their 18th birthday. More than 12 million girls are married in childhood each year and an estimate of 650 million girls and women around the world today have been married as children. Interestingly, child marriage can also be viewed as a form of child labour (Sisli & Limoncelli, 2019). This is because marital responsibilities, such as performing household chores can place significant physical demands for young girls who are still developing themselves.

The above alarming figures highlight that ending child labour and marriage is challenging. However, understanding the implications of these harmful practices on children's mental and emotional wellbeing and identifying mechanisms to eradicate them are critical for effective policy interventions. In this context, this thesis seeks to answer the following three broad research questions which form the basis of the thesis:

1. Does early marriage affect the mental health of women?

2. Does working as a child affect adolescent mental health? If so, does the effect vary with the type of work that he/she performs? What factors could mediate the long-term effects of child labour on mental health?

3. Does an unconditional in-kind transfer – a food subsidy program - provide a sufficient incentive for households to reduce the supply of child labour? Does it induce an increase in schooling of children?

1.3 Indonesia as a case study

The thesis uses Indonesia as a case study. There are two reasons that make Indonesia an ideal setting to address the above-outlined research questions: (1) the high prevalence of child labour and child marriage in Indonesia, (2) the availability of a rich data source, which are explained in detail below.

1.3.1 High prevalence of child labour and child marriage in Indonesia

With more than 250 million people, Indonesia is the fourth most populous nation in the world. As one of the largest economies in Southeast Asia, Indonesia has experienced a decline in economic growth since 2012, owing to the end of the export boom. In 2017, the country was ranked 127th among all the countries in the world in terms of its GDP per capita (in purchasing power parity), which was $12,400 (CIA, 2018).[1] As a middle-income country, Indonesia struggles with many problems such as poverty (where almost 11 per cent of its population are below the poverty line), unemployment, inequality and corruption.

In terms of demographic structure, Indonesia consists of a large child population under the age of 18 years, which accounts for almost one-third of its population (84 million).

[1] As cited in Central Intelligence Agency (24 December 2019). Retrieved from https://www.cia.gov/library/ publications/resources/the-world-factbook/geos/id.html.

However, as a less developed country, it faces many challenges in relation to ensuring a high quality of life for its children. This is because Indonesia has a high incidence of child labour, child marriage, sexual exploitation and lack of birth registration (UNICEF, 2013) which inevitably lead to an adverse impact on child wellbeing.

Across Indonesia, a total of 6.9 per cent of children aged 5 to 17 years were in child labour in 2009 (BAPPENAS & UNICEF, 2017). Alarmingly, close to half of these child workers were engaged in hazardous conditions (BAPPENAS & UNICEF, 2017). Regarding early marriage, one in 10 women (11.2 per cent) was married or in union before the age of 18 years in 2018 (BAPPENAS, 2019). In absolute terms, Indonesia has the eighth highest number of child brides in the world (BAPPENAS & UNICEF, 2019).

1.3.2 The availability of a rich data source

As a less developed country, Indonesia has the most comprehensive household data – the Indonesia Family Life Survey (IFLS). The IFLS is an ongoing longitudinal survey which is administered by the RAND organisation. Currently, there are five waves covering years 1993 (IFLS 1), 1997/98 (IFLS 2 and IFLS2+), 2000 (IFLS 3), 2007 (IFLS 4) and 2014 (IFLS 5).

The IFLS consists of several unique features. First, it is one of the few large-scale population-based surveys in operation for more than 20 years, especially in the context of a developing country. Second, in terms of representation, IFLS is a sample drawn from 13 of the country's 26 provinces which consist of 83 per cent of the Indonesian population. In IFLS1, data were collected from over 22,000 individuals in 7,224 households. By 2014, the numbers had increased to 50,000 individuals from 17,000 households. Third, there is over 85 per cent re-contact rate in each wave leading to high quality of data with relatively low attrition (Strauss et al., 2016). Finally, IFLS is a multipurpose survey which collects information at the individual, household and community level. Therefore, it includes data on a range of topics such as demographics, physical and mental health status, education, household consumption patterns and labour market outcomes which facilitate the conduct of extensive research with regard to various aspects.

1.4 Structure of the thesis

The thesis consists of three main chapters that focus on each of the three research questions outlined in Section 1.2. The second chapter examines the impact of early marriage on the mental health of women in Indonesia, using data from the two recent waves of IFLS. The mental health is assessed using one of the commonly used measures of the 10-item Centre for Epidemiological Studies Depression Scale (CES-D-10) (Andresen et al., 1994; Radloff, 1977). Following the seminal paper by Field and Ambrus (2008), existing causal studies apply an instrumental variable strategy where age at menarche is used as an instrument for early marriage. However, this study shows that using age at menarche as an IV is not valid, resulting in biased estimates. This is because the timing of menarche is said to be associated with depressive symptoms leading to a violation of the exclusion restriction.

As an alternative, this study combines several econometric methods by exploiting the panel structure of the IFLS data. Considering early marriage as the treatment variable, this study uses coarsened exact matching (CEM) with difference-in-differences (matched DD) including individual fixed effects to address the endogeneity bias of early marriage. The strength of combining methods is that it offsets the limitations of a single method resulting in a robust estimator (Gertler et al., 2011). The results reveal that early marriage has a significant adverse effect on women's mental health status. This study further examines the consistency of the results by taking age at marriage instead of the dummy variable. In this regard, correlated random effects (CRE) model and Hausman-Taylor (HT) approach are employed. The findings show that a one-year delay in marriage decreases the probability of having depression. These findings are robust to several sensitivity checks, including a placebo test with a false treatment group and Oster (2019) method for model robustness. Policy-wise, the results provide valuable insights for laws and policies targeted at ending child marriage. The findings justify the need to accelerate the progress towards eradicating early marriage. Moreover, it also highlights the need to provide the required psychological support and access to mental healthcare to those women who are married as children - an area that is often overlooked.

The third chapter of the thesis investigates the long-term effect of child labour on adolescent mental health. A major concern in identifying the causal effect of child labour on adolescent mental health is that the decision to work as a child is possibly endogenous due to factors such as omitted variables and selection bias. To correct for such potential endogeneity bias of child work, two instruments - minimum wage (Sim et al., 2017) and the number of family-owned businesses by the household are applied. Moreover, by taking advantage of IFLS as a rich data source, this study controls for a wide range of socio-demographic, childhood adversity, health status, habits and behavioural covariates that are well established in the mental health literature. Considering the nature of our main outcome variable of interest – the mental health score based on the CES-D scale, this study employs an IV-Poisson model to estimate the effect of child work on mental health. The results reveal that child labour has a substantial negative impact on the child's long-term mental health status.

The study further finds heterogeneity in the effect of child labour where working as a child for wages increases the mental health score (CES-D score), leading to depressive symptoms. On the contrary, there is no significant impact of working as a child in family enterprises on adolescent mental health. This implies that child work for wages is a worse form of child labour. The validity of estimated results depends on whether the selected IV satisfies the exclusion restriction. Therefore, by following the plausibly exogenous method proposed by Conley, Hansen and Rossi (2012), this study shows that the instruments do not violate the exclusion restriction. Given the adverse effect of child work on adolescent mental health, this chapter further attempts to understand the factors that could mediate this substantial effect, an aspect which is vital for policy responses. It is found that religiosity and social capital can play a role in mediating the adverse long-term effects of child labour on mental health.

The fourth chapter examines the impact of an 'unconditional' in-kind transfer - a food subsidy on the labour supply and schooling of children. For this purpose, this study considers one of the largest subsidised food programs known as 'Raskin' (or rice for the poor) that is currently in operation in Indonesia (Banerjee et al., 2016; Trimmer et al., 2018; World Bank, 2012). The study uses data from 1997, 2000, 2007 and 2014 waves of IFLS. The main identification issue arises from selection bias due to non-random distribution of the subsidy and unobserved heterogeneity. To address this, coarsened exact matching (CEM) with the difference-in-differences (DD) estimator is implemented.

Given that engaging in labour market activities and attending school is a joint decision that competes for a child's time, the study uses a bivariate probit model with a matched double-difference approach to estimate the effect of Raskin on the likelihood of child labour supply and school attendance, conditional on a set of individual and household characteristics.

The findings show that receiving Raskin decreases the probability of engaging solely in child labour and increases the probability of only attending school. Interestingly, Raskin decreases the probability of engaging in work and attending school simultaneously. This implies that the decrease in child labour occurs among those children who are both working and schooling, resulting in a corresponding increase in the likelihood of schooling only. The study further reveals that the effect of Raskin is heterogeneous. Specifically, it reduces work and increases schooling for boys while there is no impact on the outcomes of girls. Nevertheless, as an unconditional in-kind transfer, the ability of a food subsidy to decrease child labour of boys in a developing country provides a vital policy implication on how social protection tools can indirectly influence the wellbeing of children.

The remainder of the thesis is structured as follows. Chapter 2 examines the mental health effects of early marriage. Chapter 3 investigates whether child labour affects the long term mental wellbeing of children. Chapter 4 evaluates the effectiveness of an unconditional in-kind transfer program in addressing issues such as child labour and low schooling. Chapter 5 concludes the thesis. Chapters 2-4 are written as stand-alone papers.

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Chapter 2

Happily Ever After? Mental Health Effects of Early Marriage

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Statement of Authorship

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Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Abstract

Early marriage is a manifestation of gender discrimination against girls, leading to adverse consequences on their wellbeing. We use longitudinal data from the Indonesia Family Life Survey (IFLS) to examine how early marriage affects the mental health of women. To address the endogeneity bias of early marriage, we employ various methodologies including fixed effects, coarsened exact matching combined with difference-in-differences and instrumental variable strategy. We find that marrying early, particularly by the age of 18 years, has a strong negative effect on women's mental health. Specifically, they are 10.6 percentage points more likely to be depressed and 6.8 percentage points more likely to be affected by severe depressive symptoms. These findings add to the evidence of health effects of early marriage and provide a rationale for policy interventions implemented towards eradicating it.

Keywords: Early marriage; mental health; panel data; instrumental variable; Indonesia

JEL classification: I15, I31, J12, J16

2.1 Introduction

Early marriage is a widespread phenomenon where 1 in 5 women (21 per cent) are married before their 18th birthday.[1] More than 12 million girls are married in childhood each year, and an estimate of 650 million girls and women have been married as children globally.[2] Early marriage is an indication of gender inequality and discrimination against girls (Leeson & Suarez, 2017).[3] Girls who marry early are not only deprived of their childhood but also the opportunity to lead a better life. They are more likely to experience poor maternal health (Clark et al., 2006; Field & Ambrus, 2008) as well as lower educational attainment limiting their employment opportunities and earnings potential (Bajracharya et al., 2019; Delprato et al., 2015; Field & Ambrus, 2008; Nguyen & Wodon, 2014; Wodon et al., 2017; Yount et al., 2018). Moreover, such underage unions can further result in intergenerational effects affecting the wellbeing of their children (Adhikari, 2003; Chari et al., 2017; Finlay et al., 2011; Sekhri & Debnath, 2014; UNICEF, 2014). These impacts are often larger when the girl marries very early (Male & Wodon, 2016).

Early marriage may also have a profound effect on the psychological and emotional wellbeing of women. This is because marrying at a very young age can be a stressful and traumatic experience. Girls are often separated from their families and friends to cohabitate with their husband and his family, putting them at greater risk of social isolation (UNICEF, 2014). Marital responsibilities, such as childbearing and child-rearing, can place significant physical and mental demands on young girls who are still developing themselves (Steinhaus & John, 2018). Girls are also more likely to be victims of intimate partner violence and forced sexual relations. It is shown that girls who marry before they are 15 years old are 50 per cent more likely to be affected by physical or sexual violence from a partner.[4] According to studies in psychology, being constantly exposed to such adverse and stressful experiences can impact mental health, causing disorders such as depression, anxiety and panic attacks, which may persist into adulthood (Hammen, 2005;

[1] An early marriage where the participant is under 18 years is commonly referred to as child marriage.

[2] As cited in UNICEF (2019). Retrieved from https://www.unicef.org/stories/child-marriage-around-world

[3] According to Leeson and Suarez (2017), parents usually prefer sons over daughters. As a result, there could be more daughters in a family, leading to a higher incidence of child marriage.

[4] As cited in Girls not brides (2019). Retrieved from https://www.girlsnotbrides.org/themes/violence-against-girls/

Kendler et al., 1999; McMahon et al., 2003).

There is a growing interest in mental wellbeing recently as poor mental health among adolescents is on the rise.[5] It is estimated that 10 to 20 per cent of children and adolescents experience mental illnesses leading to poor mental health (World Health Organisation, 2018).[6] Notably, half of all chronic mental disorders start by the age of 14 and three-quarters by the age of 24 (Kessler at al., 2007). These figures reflect the importance of ensuring a safe and secure environment for teenagers and young adults.

This study examines the impact of early marriage on the mental health of women in Indonesia. In absolute terms, Indonesia has the eighth highest number of child brides in the world, with 1 in 10 women are married before the age of 18 years. Moreover, of developing countries, Indonesia has the most comprehensive household panel data – the Indonesia Family Life Survey (IFLS). Critically and uncommonly, the recent two waves of IFLS include data on mental health. Employing several identification strategies such as fixed effects, coarsened exact matching (CEM) combined with difference-in-differences and instrumental variable approach, we seek to assess the causal effect between an early marriage of a woman and her mental health status. The results reveal that early marriages have a significant negative impact on women's mental health status. More specifically, women who marry early, that is by the age of 18 years are 10.6 percentage points more likely to be depressed and 6.8 percentage points more likely to be affected by severe depressive symptoms. Additionally, we find that a one-year delay in marriage decreases the probability of having severe depression by approximately five per cent of the mean. These findings are robust to a variety of sensitivity checks.

This study makes several contributions to the literature. First, it adds to the sparse literature on the causal effects of women's marital age on their socioeconomic wellbeing. Compared to studies on educational, physical health and intergenerational outcomes of early marriage, studies on mental health effects are limited. Therefore, to the best of our knowledge, we provide first evidence on the causal effect of early marriage on mental health. The mental health is assessed using one of the commonly used measures of the

[5] The World Health Organisation (WHO) defines an adolescent as any person between ages 10 and 19 years.

[6] As cited in World Health Organisation (26 February 2019). Retrieved from https://www.who.int/mental_health/ maternal-child/child_adolescent/en/

10-item Centre for Epidemiological Studies Depression Scale (CES-D-10) (Andresen et al., 1994; Radloff, 1977). In general, longitudinal datasets which consist of data on such validated measure of mental health are scarce, particularly with regard to less developed countries. Given that early marriages are mostly a problem in developing countries, we contribute to the existing body of evidence in this area by examining the mental health effects of early marriage.

Second, our study contributes to the extensive literature on 'missing women' in developing countries (Anderson & Ray, 2010; Klasen & Wink, 2002; Sen, 1990). Developed by Sen (1990), the concept of 'missing women' refers to the low ratio of women to men in developing countries. This occurs as a result of excess mortality of women due to reasons such as gender discrimination and negligence (Anderson & Ray, 2010). Early marriage is a practice that signifies entrenched gender inequality which affects women disproportionately. Our paper highlights that early marriage results in higher depression and severe stress for women. This, in turn, can lead to detrimental consequences as individuals with mental disorders are more vulnerable to risk-taking behaviours such as self-harm. Therefore, our findings may provide a possible explanation in understanding the excess mortality of women in developing countries.

Our study differs from the existing studies on early marriage in terms of methodology. Following the seminal paper by Field and Ambrus (2008), many studies apply an instrumental variable strategy where age at menarche[7] is used as an instrument for early marriage (or child marriage). In this study, in addition to the instrumental variable approach, we combine several econometric methods by exploiting the panel structure of the IFLS data. Initially, we use a fixed-effects model to address an important source of endogeneity arising from unobserved individual heterogeneity. For instance, personal norms and attitudes may be associated with both mental health status and timing of marriage, which differ across individuals but is unobserved. Since the fixed-effects model cannot address all sources of endogeneity, we additionally use a matched difference in difference (matched DD) approach with fixed-effects to further strengthen the identification by considering early marriage as the treatment variable. The strength of combining methods is that it offsets the limitations of a single method leading to a robust estimator

[7]This is the age at which the first menstruation begins.

(Gertler et al., 2011). In particular, CEM accounts for selection bias through observed characteristics, while difference-in-differences takes care of any unobserved characteristics that are constant across time between the treatment and control groups. The inclusion of fixed effects eliminates time-invariant sources of individual heterogeneity and thus resulting in an unbiased estimator.[8]

From a policy perspective, our results provide valuable insights for laws and policies targeted at ending child marriage. Explicitly, our findings justify the need to accelerate the progress towards eradicating early marriage as the consequences of it affect not only the physical wellbeing but also the emotional wellbeing of girls. Moreover, our study also emphasises the importance of providing the required psychological support and access to mental healthcare to those women who are married as children - an area that has been often overlooked.

The remainder of the chapter is structured as follows. Section 2.2 provides a brief background on early marriage and mental health. Section 2.3 reviews the existing empirical literature. Section 2.4 describes the data source and the variables used in the study. Section 2.5 outlines the estimation strategy. Section 2.6 presents the empirical results followed by robustness checks in Section 2.7. Section 2.8 discusses the findings, and the concluding remarks are given in Section 2.9.

2.2 Background

2.2.1 Global Estimates of Early Marriage and Mental Health

The widespread practice of early marriage violates the child's right to reach her full potential. According to recent statistics, 21 per cent of young women are married before the age of 18 (UNICEF, 2018). Early marriages are most common in the regions of sub-Saharan Africa and South Asia, which together consist of the ten countries with the highest rates of child marriages (UNICEF, 2014). Sub-Saharan Africa has the highest prevalence of child marriage, where around 4 in 10 young women are married as children.

[8] See Section 2.5 for a detailed explanation on why a simple OLS regression can lead to biased results.

This is followed by South Asia, where approximately 30 per cent of girls are married as children (UNICEF, 2019).[9]

There is a declining global trend in the prevalence of early marriage, where the number of young child brides has reduced by 15 per cent during the past decade (UNICEF, 2018). Despite this downward trend, 12 million girls are married in their childhood every year, accounting for a total of 650 million child brides globally. Therefore, it is vital to accelerate the progress towards eradicating early marriage to achieve the target of ending child marriage by 2030 as set out in the Sustainable Development Goals.

The negative consequences of early marriage on the physical wellbeing of girls are well documented. However, early marriage can also lead to adverse effects on the emotional wellbeing of girls. If we consider the global estimates, in general, 10 to 20 per cent of children and adolescents experience mental disorders leading to poor mental health (WHO, 2018). The consequences of poor mental health are mainly visible during the adolescence period. For instance, depression is identified as the ninth major cause of disability among adolescents worldwide. Self-harm is the third main source of death, and alarmingly, it is the second major cause of death for girls aged 15 to 19 years (WHO, 2018)[10]. According to Kessler et al. (2007), childhood is a critical period, where half of all lifetime mental illnesses start before the age of 14. This shows the importance of ensuring a safe and secure childhood for all children.

2.2.2 Child Marriage in Indonesia

Indonesia has a high incidence of child marriage in the Asia Pacific region. According to BAPPENAS (2019), one in 10 women (11.2 per cent) was married or in union before the age of 18 years in 2018. In absolute terms, Indonesia has the eighth highest number of child brides in the world (BAPPENAS & UNICEF, 2019). One of the main reasons for early marriage in Indonesia is the Marriage Law 1974 that does not require to meet the 18 years threshold for marriage, which is generally accepted by the International Human

[9] As cited in UNICEF (2019). Retrieved from https://data.unicef.org/topic/child-protection/child-marriage/

[10] As cited in World Health Organisation (26 February 2019). Retrieved from https://www.who.int/mental_health/ maternal-child/adolescent/en/

Rights Treaty Bodies. According to the Marriage Law 1974, with parental consent, girls are allowed to marry at 16 and boys at 19 years (BAPPENAS and UNICEF, 2019). It is also possible to marry off girls even earlier by obtaining the approval from religious courts or local officials, in which case there would be no minimum age of marriage.

The prevalence of early marriage in Indonesia depends on poverty and rural residence. Girls from the poorest quintile of households are four times more likely to marry before 18 years compared to girls in the top quintile of households. Moreover, early marriages are mainly seen in rural areas, where 18 per cent of rural women are married at 18 or younger compared to seven per cent of urban women (BAPPENAS & UNICEF, 2017). Early marriage inevitably hinders education (Parsons et al., 2015). Only nine per cent of married girls under 18 years complete their senior secondary education as opposed to 54 per cent of their unmarried peers (BAPPENAS & UNICEF, 2017). This means girls who marry in childhood are six times less probable to complete their secondary education.

2.2.3 Mental Health in Indonesia

As a developing country, there exists a considerable stigma around mental health issues in Indonesia, where people with mental health problems are often stereotyped and discriminated. According to the World Health Organisation (2017), 6.4 per cent of individuals aged 15 years and above experience mental disorders in Indonesia. However, there are significant inequalities in mental and emotional disorders across dimensions such as gender, age, place of residence, economic status, education and employment status. The statistics reveal that women are more prone to mental disorders where the proportion is 7.8 per cent compared to that of 4.9 per cent of men. In terms of age profile, the percentage of individuals with poor mental health remains around 5 to 8 per cent among the age groups of 15 to 64 years. This percentage increases strikingly up to 18 per cent among the elderly (WHO, 2017).

Considering education, there is a clear difference between the least educated and most educated. Individuals with no education are four times more likely to experience poor mental health compared to individuals with higher education (WHO, 2017). Economic status and place of residence also affect mental health. Individuals from poorest quintile are two times more likely to suffer from mental disorders compared to individuals in the wealthiest quintile of households (WHO, 2017). Surprisingly, poor mental health is mainly seen in urban areas, where 6.8 per cent of individuals experience mental disorders compared to 5.9 per cent of individuals in a rural residence (WHO, 2017). These figures depict that poor mental health is, in fact, an issue in Indonesia, and thus identifying the possible causes are essential for control and prevention efforts.

2.3 Review of Literature

This study relates to the literature on the impacts of early marriage on the wellbeing of women. Parsons et al. (2015) provide a systematic review of this literature. Accordingly, early marriage has repercussions on women's socioeconomic outcomes such as lower educational attainment and labour force participation (Bajracharya et al., 2019; Jensen & Thornton, 2003; Wodon et al., 2017; Yount et al., 2018), lack of autonomy leading to domestic violence (Nasrullah et al., 2014; Rahman et al., 2014) and worse maternal health (Clark et al., 2006). This harmful practice also leads to intergenerational effects; as early marriage affects not only the woman but also her children in terms of poor health and low educational levels (Adhikari, 2003; Finlay et al., 2011; Raj et al. 2010; UNICEF, 2014).

Though there are a plethora of studies examining the effects of early marriage (or child marriage) on both women and their children, most estimate associations rather than causal effects. This could be problematic since the effect of early marriage on outcomes such as education or health could be endogenous due to factors such as unobserved heterogeneity, reverse causality or selection bias. The seminal paper by Field and Ambrus (2008) addresses this concern by utilising age at menarche as an instrumental variable. Drawing from biological research, they argue that genetic factors play an important role in determining the timing of puberty and the fact that these genetic variations are random makes it a good instrument. Moreover, Field and Ambrus (2008) provide strong empirical evidence on the positive relationship between age at menarche and marriage decision. Based on this strategy, they show that early marriage results in lower educational attainment for women in terms of schooling years and literacy as well as the use of antenatal health care practices in Bangladesh.

Following Field and Ambrus (2008), few studies have used age at menarche as an instrument to isolate the causal effect of early marriage on various outcomes. For instance, Chari et al. (2017) and Sekhri and Debnath (2014) show the intergenerational impacts of women's age at marriage in India. They find that delayed marriage leads to better outcomes for children in terms of their education and health. In another study in India, it is shown that delayed marriage leads to a reduction in domestic violence, especially that of physical violence (Dhamija and Roychowdhury, 2018). Using longitudinal data from Bangladesh, Asadullah and Wahhaj (2018) provide causal evidence on how early marriage can lead to increased transmission of traditional gender norms.

In contrast to the above, a limited number of studies have used different instruments. For example, using child marriage measures at the primary sampling unit (PSU) as instrumental variables, Nguyen and Wodon (2014) examine the effect of early marriage on schooling attainment and literacy in Africa. The authors suggest that such PSU-level instruments could be used as an alternative in the absence of data on menarche, which is often the case with many multi-purpose surveys. On the other hand, Ramnarine (2017) uses drought and flood shocks as an instrumental variable for age at marriage. Based on data from Bangladesh, this study also finds that early marriages have long term implications where children from early marriages are more likely to be stunted.

The above studies highlight that the instrumental variable approach is the key identification strategy employed to isolate the causal effects of early marriage. However, Hombrados (2017) argues that there could be potential limitations in using this approach. Especially, employing age at menarche to instrument early marriage could be problematic as it might not fully satisfy the exclusion restriction. Therefore, as an alternative identification strategy, Hombrados (2017) applies a regression discontinuity design (RDD), which exploits the change of legal marital age of women from 15 to 18 years in Ethiopia to identify the causal effect of child marriage on infant mortality. The findings suggest that the increase in legal marital age had significant effects on reducing both child marriage and infant mortality. Specifically, a one-year delay in women's age at marriage decreases the probability of infant mortality of the first-born child.

Another gap in early marriage literature is the non-existence of empirical evidence on the causal effect of early marriage on women's mental health (Parsons et al., 2015). It is a well-known fact that girls who marry early tend to experience a higher risk of isolation, depression and panic attacks than those married later, due to adverse consequences such as lower education, increased domestic violence and poor health (Parsons et al., 2015). This is further established by studies such as Gage (2013); Le Strat et al. (2011) and Steinhaus and John (2018), which provide strong evidence that marrying particularly at a very young age leads to poorer mental health among women in both developed and developing countries. None of these studies establish a causal effect.

To the best of our knowledge, our study is among the first to examine the causal effect of early marriage on women's mental health in a developing country context. Contrary to previous studies, we combine several identification strategies to address the potential endogeneity of women's age at marriage. Therefore, our study seeks to address both the evidence and methodological gaps in early marriage literature.

2.4 Data

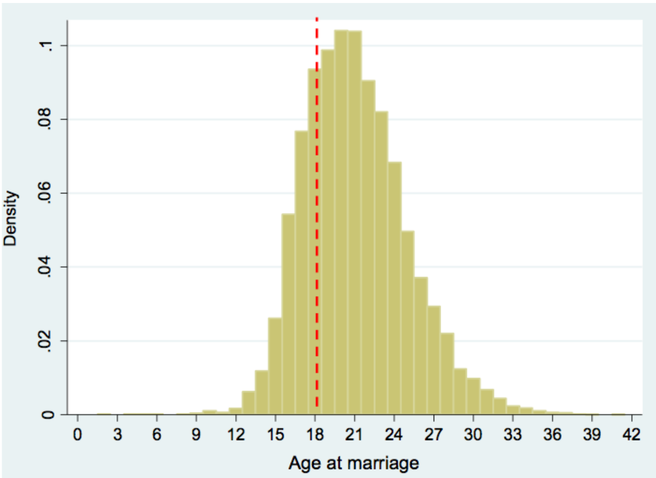
2.4.1 Data Source and Sample of Interest

The empirical analysis is based on data from the Indonesia Family Life Survey (IFLS). The IFLS is an ongoing longitudinal survey with low attrition (see Section 1.3.2). Currently, there are five waves covering years 1993 (IFLS 1), 1997/98 (IFLS 2 and IFLS2+), 2000 (IFLS 3), 2007 (IFLS 4) and 2014 (IFLS 5). This study uses data from the 2007 and 2014 waves of the IFLS since information on mental health is collected for the first time in 2007.

Our sample is restricted to women between ages 15 and 35 years in 2007 and are also surveyed in the 2014 wave. The minimum cut-off point of 15 years is chosen as the questions on mental health and marital history are available only for individuals who are 15 years and above. Following Field and Ambrus (2008), we select the maximum age of 35 years to minimise censoring of women who either marry late in life or those who have changes in marital status such as remarriage due to separation or divorce. The sample of women is also restricted to those who are either unmarried or married once. This means married women who are either separated, divorced or widowed are excluded from our sample (which accounts for about one per cent of the total sample) to avoid biased estimates. However, as a robustness check, we relax both of these age and marital status restrictions.

Our sample consists of 11,538 observations from 5,769 women. After excluding observations with missing responses, 11,211 observations are used in the estimation. Thirty per cent of the women are married by the age of 18 years. Figure 2.1 illustrates the distribution of age at marriage for married women in our sample.

Figure 2.1: Distribution of Age at Marriage



Note: This figure is based on data from IFLS 4 (2007) and IFLS 5 (2014) waves.
The dotted line at 18 years represents the generally accepted threshold for marriage.

2.4.2 Early Marriage Status

The data on marital history are extracted from the marital history module of IFLS, which is administered to ever-married women aged 15 years and above. As our main variable of interest, we construct a binary variable which takes on a value of 1 if the woman was married by the age of 18 years to denote early marriage, and 0 otherwise. In contrast to previous literature on early marriage, we use a binary variable instead of age at marriage for three main reasons. First, this allows us to include both married and unmarried women in our sample resulting in an unbiased sample selection. However, due to the inclusion of unmarried women, an indicator that takes on a value of 1 if the woman is married and 0 otherwise is used as a control variable to distinguish between women who marry late and unmarried. We also control for the number of years in marriage as the effect of marriage on mental health can vary based on whether the woman is newly married or not.

Second, we believe that using a dichotomous variable to denote early marriage is more appropriate than using the age at marriage. This is because the coefficient of age at marriage is interpreted as the 'average effect' of delaying marriage by an additional year on the outcome variable, which is assumed to be constant at every point of the age at marriage distribution. When considering the previous causal studies on early marriage, it is evident that the distribution of age at marriage spans within a considerable range. These are summarised in Table 2.1. However, the effect of marriage for a woman with an early marriage (before 18 years) is quite different from that of a woman with a non-early marriage (for instance, at 24 years). Therefore, using an indicator variable rather than age at marriage provides a more well-defined measure of early marriage, while allowing flexibility in terms of capturing the mental health effects of those who married early and not.

Table 2.1: Distribution of age at marriage of previous studies

Study	Mean	Std Dev.	Range*	
			Min	Max
Chari et al. (2017)	18.57	3.48	12	26
Dhamija & Roychowdhury (2018)	18.23	2.63	13	23
Field & Ambrus (2008)	15.74	n/a		
Sekhri & Debnath (2014)	17.31	3.55	10	24
Asadullah & Wahhaj (2018)	16.46	0.312	16	17

*Assuming the age at marriage follows a normal distribution, range is calculated as two standard deviations above the mean and two standard deviations below it (i.e 95% of the observations).

Third, the use of a binary variable allows variation in marital status between the two waves facilitating fixed effects estimation. As shown in Table 2.2, four per cent of women in our sample who are not married in the first wave are married by the age of 18 years during the next wave. The use of fixed effects estimation addresses an important source of endogeneity by eliminating unobserved individual-specific effects or heterogeneity.[11] Age at marriage does not allow fixed effects approach since it is a time-invariant variable. However, as a robustness check, we estimate a separate model considering age at marriage as the main variable of interest. In this regard, we employ correlated random effects (CRE) and Hausman Taylor estimation technique to allow for both time-invariant covariates and individual heterogeneity.

Table 2.2: Transition probabilities for early marriage

Early marriage = 1 if married by the age of 18 in wave 1 (2007)	Early marriage = 1 if married by the age 18 in wave 2 (2014) 0	1	Total
0	3,892	160	4,052
	(96.0)	(4.0)	(100.0)
1	0	1,627	1627
	(0.0)	(100.0)	(100.0)
Total	3,892	1,787	5,679
	(68.5)	(31.5)	(100.0)

Note: The percentages in parenthesis sum up to 100 across columns.

2.4.3 Outcome Variable

Mental health status is assessed using the 10-item Centre for Epidemiological Studies Depression Scale (CES-D-10), which is a self-reported measure of depression based on ten questions (Radloff, 1977). As a validated scale, it has a consistent performance in both developed and developing countries (Mackinnon et al., 1998) and thus widely used in research.

The ten questions refer to how often the respondent experienced each of the depressive symptoms during the past week. All questions include four response categories 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) (Radloff, 1977). The CES-D score is calculated by obtaining the sum of these ten responses, with positively phrased

[11] We did a sensitivity analysis using 16 years as the cut-off. However, due to concerns about small sample bias (as there are only 40 women married by the age of 16 years), the results are not reported.

statements reverse-coded[12]. This ranges from 0 (no depression) to 30 (severe depression), meaning a higher score reflects a higher level of depressive symptoms. We construct three dependent variables based on the CES-D scale. First, we use the composite score of the ten questions. Second, we use an indicator variable for depression that takes on a value of one if the CES-D score is 10 and above and zero otherwise (Andresen et al., 1994). Third, we construct another dummy variable for severe depressive symptoms which is assigned a value of one if the score if greater than 15 and zero otherwise (Peltzer & Pengpid, 2018).

2.4.4 Other Covariates

Given that there are significant differences in the prevalence of poor mental health across several dimensions (as discussed in Section 2.2.3), we control for a battery of variables to capture them. These are classified as demographics, work status, education, economic and health status. Demographics include age, religion and height measured in centimetres. Work status refers to whether the woman is employed, unemployed, schooling, house-keeping or retired/sick, which are denoted as indicator variables. Similarly, dummy variables are used to control for the level of education that vary from no education to tertiary education. Since the family history of mental disorders increases the risk for depression (Levinson, 2006; Weissman et al. 2016), we include mental health scores of the parents as control variables.[13]

The monthly per capita expenditure is used as a proxy for economic status. This includes both food and non-food expenditure. As poverty is considered to be an important determinant of mental health (Currie, 2009; Dzator, 2013; Myer et al., 2008; Tampubolon & Hanandita, 2014) we also consider dwelling conditions such as whether the household uses nearby river, land or sea as the toilet and uses firewood for cooking as proxies for poverty.

Mental health also depends on physical health status (Liew, 2012). To account for physical health, we include controls such as the number of acute morbidities experienced

[12]See Table A1 in Appendix for the sample questionnaire.

[13]Due to many number of missing observations in relation to parents' mental health scores (both father and mother), we construct two dummy variables indicating the missing values.

during the last four weeks, self-reported health status, the number of days missed during the last four weeks in primary activity due to poor health and whether the individual has been confined to bed or home.

The prevalence of poor mental health in Indonesia varies based on place of residence and regional provinces (WHO, 2017). Therefore, we consider the regional heterogeneity by including dummy variables for urban/rural residence as well as individual provinces. Table A2 provides a complete list of variables used in the study.

2.4.5 Descriptive Statistics

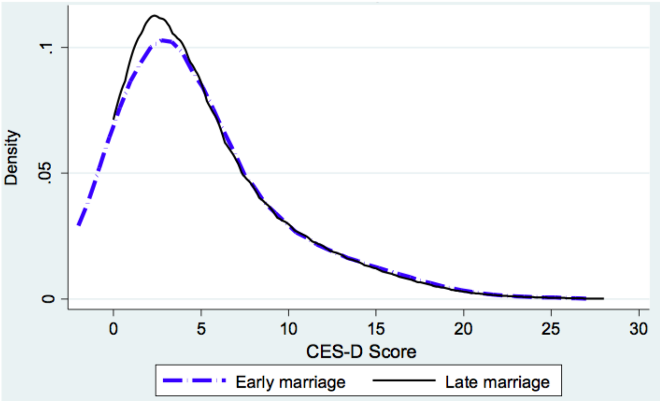
Descriptive statistics are shown in Table A3.1 in Appendix. The average mental health score of our sample is 4.9. A CES-D score of 10 or above (based on the 10-item scale) indicates the presence of clinical depression (Andresen et al., 1994). Fifteen per cent of women experience depressive symptoms, and four per cent are reported to have severe depression. The sample means of mental health score for child brides and non-child brides are also shown in Table A3. Interestingly, there is no significant difference between the mean values of mental health score or level of depression between the two groups.[14] Figure 2.2 presents the distribution of the CES-D score by early marriage status. On average, both groups depict similar distributions. However, the distribution for late marriages has a higher density at lower CES-D scores, suggesting lower depressive symptoms on average compared to the early marriage group.

Table A3 also reports descriptive statistics of other covariates. The average age is 28.5 years, and the average age of first marriage is 21 years. Nearly half of the women live in an urban area (56 per cent) and are housekeepers (49 per cent). Child brides are significantly different from non-child brides in several dimensions. As expected, women who marry early have low levels of education. Specifically, 80 per cent of those with an early marriage have only completed school up to junior level whereas 64 per cent of women who marry later have completed either senior or tertiary education. In terms of work status, women with an early marriage tend to be housewives (61 per cent) in comparison to women with a delayed marriage who are more likely to be employed (42

[14]We also present the sample means by waves for the full sample and treated and control groups. See Table A3.2.

per cent). Furthermore, it is apparent that those marry early are from poor households, as shown by variables such as per capita expenditure and household characteristics. The fact that the mental health status of parents is significantly different between the two groups highlights the presence of unobservable differences. This implies that ordinary least squares (OLS) could lead to biased estimates on the effect of early marriage on mental health.

Figure 2.2: The Distribution of Mental Health Score



Note: This figure is based on data from IFLS 4 (2007) and IFLS 5 (2014) waves.

2.5 Estimation Strategy

The objective of this study is to estimate the causal effect of early marriage on the mental health of women. From an empirical viewpoint, this is challenging due to endogeneity of the early marriage variable. To address this, we apply three estimation approaches. As our main identification strategy, we use a panel fixed effects model. Since fixed effects do not address all sources of endogeneity, we employ coarsened exact matching with difference-in-difference estimator and an instrumental variable framework for two subsamples, which are explained in detail below.

2.5.1 Panel Fixed Effects Model

As our first strategy, we exploit the panel structure of the IFLS data to estimate the effect of early marriage on mental health. By using a binary variable to denote early marriage, we estimate the following fixed effects model to identify the mental health effects of early marriage:

$$MH_{it} = \alpha + \beta EM_{it} + \eta \mathbf{X}_{it}^{'} + \varphi_i + \varepsilon_{it} \tag{1}$$

where MH_{it} is the mental health status (either CES-D score or indicator variables as described above) of woman i in year t. Our main independent variable is EM_{it}, which is a dummy variable that equals to 1 if the woman i is married by the age of 18 years in year t and 0 otherwise. $\mathbf{X}_{it}$ is a vector of covariates representing demographics, work status, education, poverty and health status of woman i in year t. φ_i denotes unobserved time-invariant individual-specific effects and ε_{it} is the error term.

There are several sources of individual time-invariant fixed effects that could lead to biased estimates. For instance, genetic health endowments of the individual woman can influence both the health status and timing of marriage. Healthier girls, both physically and emotionally are more likely to marry early than those who are not.[15] Moreover, they also tend to be emotionally stable in the long run and events such as an early marriage may not have a considerable effect on their mental health. This means such forms of unobserved heterogeneity can lead to a positive relationship between early marriage and mental health. On the other hand, family norms and attitudes towards children can also affect marriage decisions. Parents who are more concerned about the wellbeing of their children are less likely to marry off their daughters early. Besides, they are also likely to allocate more resources to improve the child's health (Leeson and Suarez, 2017). Therefore, such favourable attitudes of a family could create a negative relationship between early marriage and mental health. The fixed-effects model could deal with these types of selection bias, allowing us to consistently estimate β - the effect of early marriage on mental health. Using within transformation or mean differencing, it eliminates φ_i in equation (1) which denotes unobserved time-invariant individual fixed effects that could be possibly correlated with both the marriage decision and mental health of the woman (Cameron and Trivedi, 2009).

[15] This claim is developed based on the concept of 'healthy worker selection effect' proposed by (O'Donnell et al., 2005).

2.5.2 Coarsened Exact Matching (CEM) Combined with Difference-in-differences (DD) Estimator

One caveat of the above fixed effects model is, it can only address endogeneity due to unobserved time-invariant individual heterogeneity. Therefore to strengthen our identification strategy, we employ a difference-in-differences (DD) estimator with panel fixed effects as our second econometric technique.

To employ the DD technique, we restrict our sample to women who are either unmarried or not had an early marriage in wave 4 (2007) and are also observed in wave 5 (2014). The purpose of such restriction is to create a set up where a subsample of women is exposed to the treatment (i.e. had an 'early marriage') in the second time period (wave 5) but not in the first period (wave 4). This would represent our treatment group. The remaining group of women who are not exposed to the treatment (i.e. no early marriage) during either period would be the control group.

By using the double-difference estimator, we seek to rule out two potential endogeneity concerns. First, we control for both observed as well as unobserved time-invariant factors in the treatment group by comparing the before-and-after mental health outcomes (the first difference) of those who married early (Gertler et al., 2011). Second, to account for omitted time-varying factors such as changes in socioeconomic conditions which can have an impact on mental health, we compare this first difference with the same estimate for a group of women who did not have an early marriage resulting in a double difference estimator (Muralidharan & Prakash, 2017).

One of the key identifying assumptions of DD is that the mental health *trends* would be the same in both groups in the absence of treatment (early marriage), which is referred to as the parallel trend assumption (Angrist & Pischke, 2009). Given that our sample is confined to only two time periods, we are unable to investigate the changes in mental health outcomes for the treated and control groups before treatment. However, as a robustness check, we perform a placebo test using a false treatment group to assess the validity of this assumption (Gertler et al., 2011).

Another concern in estimating the treatment effect is the non-random assignment of the treatment resulting in selection bias. Girls married early, for instance, may come from poorer households, which in itself may affect mental health. Further, early marriage can also be a result of other social, religious and cultural aspects which in turn can affect mental health. This suggests that the outcomes of girls who marry early and those who do not would differ even in the absence of being married early leading to biased estimates. Hence, to deal with such treatment selection bias, we use coarsened exact matching (CEM) to create a control and a treatment group that are similar on observable characteristics. According to Blackwell et al. (2009), the underlying mechanism of CEM is to exactly match the treatment and control groups by temporarily coarsening variables and use the original values of the matched units for regression. Compared to other matching techniques, CEM has the ability to reduce model dependence, imbalance, estimation error and bias (Iacus et al., 2012).

By using the weights generated by the CEM process, we estimate the following fixed effects DD model:

$$MH_{it} = \alpha + \gamma EM_{it} + \delta Post_{it} + \beta EM * Post_{it} + \eta \mathbf{X}'_{it} + \varphi_i + \varepsilon_{it} \tag{2}$$

where MH_{it} is the mental health status (either CES-score or indicator variables as described above) of woman i in year t. EM_{it}, is a dummy variable that equals to 1 if the woman i is married by the age of 18 years in year t and 0 otherwise, $Post_{it}$ is an indicator variable which takes on a value of 1 for wave 5 (2014) and 0 for wave 4 (2007). Our variable of interest is $EM * Post_{it}$ which equals to 1 if the woman i had an early marriage in wave 5 (2014) and 0 otherwise. $\mathbf{X}_{it}$ is a vector of covariates representing demographics, work status, education, poverty and health status of woman i in year t. φ_i denotes unobserved time-invariant individual heterogeneity and ε_{it} is the error term.

The strength of the above model lies in that fact that it combines three different econometric techniques that address different sources of endogeneity, resulting in an unbiased estimator. More specifically, panel fixed effects consider unobserved individual heterogeneity, CEM deals with selection bias, whereas DD estimator accounts for possible changes in trends. Therefore, it can be argued that the coefficient of the interaction term β - denotes the causal effect of early marriage on the mental health of women.

2.5.3 Instrumental Variable Framework

Following previous causal studies of early marriage, we employ an instrumental variable approach as our third strategy. As proposed by Field and Ambrus (2008), we select age at menarche as an instrument for early marriage.[16] As a result, our sample of interest is restricted to married women as data on menarche are only reported for them. Though an FE-IV would have been the ideal model to estimate, it is not feasible since age at menarche is a time-invariant variable. Therefore, we estimate two-stage least squares (2SLS) and random effects IV regressions. Both of these techniques exploit the variation in age at menarche to identify the causal effect of early marriage on mental health. An ideal instrument is one that induces variation in marriage timing exogenously (relevance) and affects the outcome of interest (mental health) only through early marriage (exclusion restriction). Therefore, we discuss these two conditions in detail below.

2.5.3.1 Validity of the Instrument

According to Field and Ambrus (2008), age at menarche can influence the decision of marriage. Though various factors could lead to an early marriage of a woman such as poverty, cultural and religious beliefs, it is shown that such underage unions are usually withheld until puberty (Field and Ambrus, 2008). Once a girl reached menarche, it is customary for the parents to marry off her soon so as to avoid any unwanted pregnancies (Chari et al., 2017). This is especially true in less developed countries such as Indonesia, India and Bangladesh, where marriages are mainly governed by cultural and religious traditions. This suggests an increase in age at menarche could lead to delayed marriages for women and thereby the relevance of the chosen instrument.

When we look at the determinants of age at menarche, biological research shows that genetic factors play an important role in adolescent development including the timing of puberty, rather than family background and environmental factors (Kaprio et al., 1995). The fact that these genetic variations are random makes the age at menarche a good instrument to obtain exogenous variation in the decision to marry early or late.

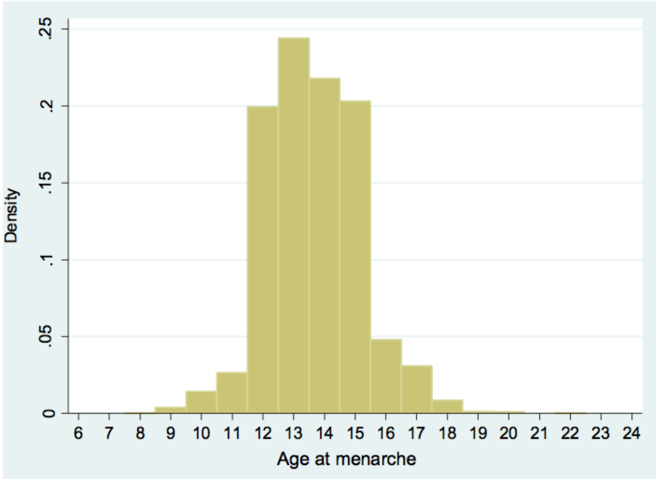
[16] Studies such as Chari et al. (2017) and Sekhri and Debnath (2014) have also used age at menarche as an IV for early marriage of women.

Nevertheless, it is argued that external factors such as poor physical health and nutrition status, hard physical labour or stress, exposure to environmental toxins, adverse climate and geographic conditions also could lead to a change in hormonal levels affecting the onset of puberty to a certain extent. This means, women with a late marriage may be affected by malnutrition, severe stress and/or unfavourable environmental factors which could ultimately affect mental health status, thus violating the exclusion restriction. To address this concern, we use several strategies.

First, by following Field and Ambrus (2008), we include woman's height as a control variable in our estimating equation. Provided that height is a potential determinant of one's health and nutrition status, controlling for it would ensure that it will eliminate any confounding effect from health or malnutrition status on menarche and marriage conditions (Chari et al., 2017). Additionally, we also control for woman's physical health status using several covariates to minimize the effect of physical health on mental health. Second, we include provincial fixed effects to account for the environmental factors that could affect menarche (Chari et al., 2017).

Another concern of age at menarche is recall bias leading to potential measurement error. Given that girls in less developed countries consider menarche as an important life event (Dammery, 2016), respondents are more likely to remember it accurately. To further support this argument, we derive the distribution of age at menarche. Figure 2.3 depicts a fairly normal distribution. According to Chari et al. (2017), a distribution without any bunching at certain ages, such as the school leaving age implies low recall bias.

Figure 2.3: Distribution of Age at Menarche



Note: This figure is based on data from IFLS 4 (2007) and IFLS 5 (2014) waves.

2.5.3.2 Two-stage Model

Based on the instrumental variable approach, we estimate the two-stage model below to identify the mental health impact of early marriage:

$$MH_i = \alpha + \beta EM_i + \eta \mathbf{X}_i^{'} + \varepsilon_i \tag{3}$$

and

$$EM_i = \gamma + \delta AgeMenarche_i + \psi \mathbf{X}_i^{'} + \upsilon_i \tag{4}$$

where equations (3) and (4) are the structural and first stage equations respectively. MH_{it} is the outcome of interest - mental health status of woman i. EM_i, is the dummy variable that equals to one if the woman is married by the age of 18 years and zero otherwise. $\mathbf{X}_i$ is a vector of covariates representing demographics, work status, education, poverty and health status of woman i and ε_i is the error term. $AgeMenarche_i$ denotes the age at menarche of woman i, being the instrumental variable in our estimation.

2.6 Empirical Results

2.6.1 Fixed Effects Model Estimations

We start our empirical analysis with fixed effects estimations using an indicator variable for early marriage. We estimate three separate equations considering the dependent variable as; (1) the composite score on CES-D scale (higher scores indicate higher levels of depression), (2) an indicator for depression that takes the value of 1 if the CES-D score is greater than 10, and (3) another indicator for severe depressive symptoms that takes the value of 1 if the CES-D score is greater than 15. Table 2.3 presents the results. As a benchmark, we also report the ordinary least squares (OLS) and random effects (RE) estimates. The estimated coefficients from both OLS and RE models are small and statistically not significant from zero. As discussed in section 2.5.1, these OLS and RE estimates might be downward biased, reflecting endogeneity due to unobserved characteristics that affect both mental health and the decision to have an early marriage. Fixed effects estimates eliminate the effect of such individual heterogeneity, allowing us to identify the true effect of early marriage on the mental health of women.

The estimation results of the fixed effects specification are reported in Columns 7, 8 and 9 of Table 2.3. Women who marry early are more likely to develop depressive symptoms. On average, early marriage leads to an increase in mental health score (based on the CES-D scale) by approximately 1.2 points, which is statistically significant at 5% level. Given the sample mean score of 4.9, this translates into a 25 per cent increase. When considering the two depression indicators, a similar result is observed. Those who marry early are 10.6 percentage points more likely to be depressed and 6.8 percentage points more likely to be affected by severe depressive symptoms. The fact that these fixed-effects estimates are significantly different from those estimates derived from both OLS and random effects imply that the unobserved time-invariant individual-specific effects have a considerable impact on women's mental health. This is further supported by the Sargan-Hansen statistic (see Table 2.3), which strongly rejects the null hypothesis.[17] This suggests that the time-invariant unobservables and regressors are possibly correlated, meaning a fixed-effects estimation is more appropriate.

[17]According to Cameron and Trivedi (2009), the standard Hausman test is invalid in the presence of cluster-robust standard errors. Therefore, the reported Sargan-Hansen statistic is obtained by the user-written command *xtoverid*.

Table 2.3: Effect of early marriage on mental health - OLS, RE and FE results

Variables	OLS			Random Effects			Fixed Effects		
	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early marriage	-0.038	-0.000	0.006	-0.019	0.001	0.006	1.211**	0.106**	0.068**
	(0.125)	(0.010)	(0.007)	(0.125)	(0.010)	(0.007)	(0.527)	(0.048)	(0.029)
Other covariates		Yes			Yes			Yes	
Province FE		Yes			Yes			Yes	
Year FE		Yes			Yes			Yes	
Individual FE		No			No			Yes	
Observations		11,211			11,211			11,211	
No. of individuals		5,675			5,675			5,675	
R-squared	0.228	0.138	0.063	-	-	-	0.278	0.161	0.068
Fixed vs random effects									
Ho: Random effects model									
Sargan-Hansen statistic							135.681	101.713	65.688
p-value							0.000	0.000	0.000

Robust standard errors in parentheses, clustered at individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Early marriage is denoted as a binary variable which takes on a value of 1 if the woman is married by the age of 18 years and 0 otherwise. Higher CES-D score reflects more pronounced depressive symptoms. See Table A4 for comprehensive results.

Table A4 in Appendix further reveals important insights about the determinants of mental health of women. Notably, physical health conditions as proxied by the number of acute morbidities, self-reported health status, number of days missed in primary activity due to poor health and whether the individual has been bedridden are all significant determinants confirming the strong relationship between physical and mental health. An increase in the number of acute morbidities increases the CES-D score and the likelihood of having depression and severe depression. Women who self-reported to be physically healthy are eight percentage points less depressed, and five percentage points less likely to be affected by severe depression. In line with previous studies such as Liew (2012) and Scheffel and Zhang (2018), this clearly shows that deterioration of physical health leads to poor mental wellbeing.

Apart from physical health status, woman's age and the number of years since marriage also determine the mental health status of a woman. An increase in age by one year increases the CES-D score by 0.3 points and the probability of being depressed by three percentage points. However, age does not significantly affect the likelihood of having severe depression. In contrast to age, the number of years been married have a negative relationship with mental health. An additional year in marriage decreases the CES-D score by 0.1 points and the probability of having both depression and severe depression by approximately one percentage points.

2.6.2 Matched Difference-in-differences Estimation Results

The main analysis exploits the panel structure of IFLS data through fixed effects estimation to identify the effects of early marriage on mental health. As our second identification strategy, we employ fixed effects with difference-in-differences (DD) estimator. Table 2.4 reports the results. The estimated coefficient of EarlyMarriage*Post denotes the effect of early marriage on mental health of women which is the treatment effect. As expected, the OLS coefficients are low, reflecting endogeneity bias due to unobserved heterogeneity (see Columns 1, 2 and 3). This is addressed through fixed effects. The fixed effects DD estimates (Columns 4, 5 and 6) are quite similar to that of previous results in both the magnitude and statistical significance.

As discussed in section 2.5.2, to deal with sample selection bias, we combine coarsened exact matching with difference-in-differences (matched DD) to obtain the unbiased treatment effect. The initial step of CEM is to select the pre-treatment covariates to match the treated and control individuals. To this end, we identify the significant covariates in wave 4 that determine an early marriage (i.e. treatment) in wave 5 based on an OLS estimation. (see Table A6 in Appendix). Accordingly, we select age, quadratic of age and religion for exact matching. Table A7 in Appendix provides the matching outcomes. The total of 160 girls who are married early are matched to 1,336 girls who do not fall into the category of early marriage. To diagnose the quality of the matching outcomes, we assess the covariate balance of the two subsamples - both pre- and post-matched. Table A8 in Appendix reports the results. The overall multivariate imbalance reduces from 0.35 to zero, meaning perfect balance. There is also a substantial decrease in the univariate imbalance for each of the covariates. Furthermore, there are no significant post-match mean differences between the treated and control groups, indicating a reasonable match by CEM. Columns 7, 8 and 9 of Table 2.4 report the DD estimates with the weights generated by the CEM process. The coefficients of the treatment effect are significant and larger in magnitude when compared to DD estimates without matching. This implies that matching addresses an important source of endogeneity.

Table 2.4: Effect of early marriage on mental health - DD estimates

Variables	OLS			Fixed Effects			Matching and FE		
	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early marriage	-0.042	0.006	-0.013						
(treated)	(0.324)	(0.028)	(0.012)						
Post treatment	2.839***	0.163***	0.053***	1.788*	0.047	0.011	1.210	-0.104	-0.126
	(0.113)	(0.010)	(0.006)	(1.038)	(0.089)	(0.050)	(2.584)	(0.253)	(0.135)
EarlyMarriage*Post	0.730	0.057	0.046*	1.160**	0.096**	0.062**	2.625***	0.190**	0.117**
	(0.500)	(0.045)	(0.027)	(0.533)	(0.049)	(0.029)	(0.884)	(0.077)	(0.048)
Other covariates		Yes			Yes			Yes	
Province FE		Yes			Yes			Yes	
Individual FE		No			Yes			Yes	
R-squared	0.228	0.142	0.066	0.274	0.162	0.069	0.318	0.212	0.110
Observations	7,988	7,988	7,988	7,988	7,988	7,988	2,948	2,948	2,948
No of individuals	4,048	4,048	4,048	4,048	4,048	4,048	1,495	1,495	1,495

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. Higher CES-D score reflects more pronounced depressive symptoms. See Table A5 for comprehensive results.

2.6.3 Instrumental Variable Estimation

The instrumental variable (IV) estimates are reported in Table 2.5. It is important to note that these estimation results are based on the sample of married women, and thus are not directly comparable to fixed effects regressions.[18] First, we look at the first stage regressions (see Panel B) as they provide important diagnostic tools to assess the validity of the selected instrument. It is evident that age at menarche is a strong determinant of early marriage. As expected, a one-year delay in menarche decreases the probability of having an early marriage by one percentage point. The Kleibergen-Paap F-statistic of 17.16 suggests that it is a strong instrument.[19]

Table 2.5: Effect of early marriage on mental health - IV estimates

Variables	2SLS			IV with Random Effects		
	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Early marriage	-0.104	-0.142	-0.184	-0.080	-0.142	-0.182
	(2.457)	(0.210)	(0.139)	(2.455)	(0.210)	(0.138)
Observations	10,154	10,154	10,154	10,154	10,154	10,154
No. of individuals	5,133	5,133	5,133	5,133	5,133	5,133
Panel B						
Age at menarche	-0.011***	-0.011***	-0.011***			
	(0.003)	(0.003)	(0.003)			
Kleibergen-Paap F-statistic	17.16	17.16	17.16			
Panel C - Test of Endogeneity						
Ho: Variables are exogenous						
Robust regression	0.0027	0.3549	1.8022			
p-value	0.958	0.551	0.180			

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. The Stock-Yogo critical values for 10%, 15% and 20% maximal IV size are 16.38, 8.96 and 6.66 respectively. Early marriage is denoted as a binary variable which takes on a value of 1 if the woman is married by the of 18 years and 0 otherwise. All estimations include province and year fixed effects as well as full set of control variables. Higher CES-D score reflects more pronounced depressive symptoms. See Table A9 for comprehensive results.

Despite the validity of the instrument, it can be observed that the coefficient of early marriage in all the estimations are statistically not significant from zero (Panel A).

[18] This is because data on age at menarche are reported for only those women who are in the marital history module of IFLS.

[19] In contrast to the Cragg-Donald F test, the Kleibergen-Paap F-statistic does not assume that the standard errors are *iid* when identifying weak instruments.

Subsequent to two-stage least squares (2SLS) estimation, we perform a Wald test. The test statistic strongly rejects endogeneity of early marriage (Panel C). The possible reasons as to why the IV approach leads to insignificant estimates are discussed in Section 2.8.1.

2.7 Robustness Checks

2.7.1 Placebo Test - False Treatment Group

The validity of the difference-in-differences (DD) results reported in Table 2.4 depends on the underlying assumption of parallel trends. To test this strong assumption, we perform a placebo test by considering a false treatment group (Gertler et al., 2011). We consider marrying between the ages of 19 to 21 as early marriage and follow the same procedure as discussed in Section 2.5.2.[20] In general, 18 is considered as the minimum age at marriage. Thus by estimating a difference-in-differences using the subsample of women who marries between 19 to 21 years as the false treatment group and the remaining group of women (that is, those who marry above 21 years) as the comparison group, we expect to find an insignificant or no impact on mental health.

Table 2.6 presents the results. In line with our expectations, treating those married between 19 to 21 years as early marriage has no effect on mental health across all three specifications and outcomes except the treatment effect presented in Column 1 for CES-D score. However, as an OLS estimate, this could be biased due to omitted individual fixed effects. Despite statistical insignificance, the negative treatment effects suggest that marrying between the ages of 19 to 21 has a positive effect on mental health. This is not surprising, given that it is customary for the women in Indonesia to marry in their early twenties (Utomo, 2014). Taken together, the placebo test provides suggestive evidence on the validity of the parallel trends assumption, that is, those who marry early (i.e. by the age of 18 years) and those who do not have similar mental health trends in the absence of the treatment.

[20] The estimation sample excludes the actual treatment group of women with an early marriage.

Table 2.6: Robustness check: Placebo test with a false treatment group

Variables	OLS			Fixed effects			Matching and FE		
	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Marriage	0.948***	0.056**	0.027*						
(false treatment)	(0.318)	(0.025)	(0.016)						
Post treatment	2.798***	0.163***	0.055***	1.980	0.038	0.024	1.808	0.027	-0.021
	(0.136)	(0.012)	(0.007)	(1.249)	(0.108)	(0.059)	(1.985)	(0.175)	(0.099)
Marriage*Post	-0.812**	-0.058	-0.023	-0.657	-0.040	-0.023	-0.594	-0.043	-0.009
	(0.410)	(0.038)	(0.023)	(0.449)	(0.042)	(0.025)	(0.524)	(0.048)	(0.028)
Other covariates		Yes			Yes			Yes	
Province FE		Yes			Yes			Yes	
Individual FE		No			Yes			Yes	
R-squared	0.230	0.144	0.071	0.267	0.160	0.074	0.285	0.188	0.088
Observations	6,010	6,010	6,010	6,010	6,010	6,010	4,641	4,641	4,641
No. of individuals	3,048	3,048	3,048	3,048	3,048	3,048	2,355	2,355	2,355

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. See Table A10 for comprehensive results.

2.7.2 Restricting the Sample to only Married Women

The sample of interest used in our analysis consists of both married and unmarried women. However, including women who are unmarried in both periods may raise a concern of biased estimates, especially when deriving inferences from the matched DD estimation. This is because an unmarried woman would not be a perfect counterfactual to a woman who had an early marriage. To allay this concern, we perform a robustness check by restricting the sample to only those women who are married at least in one period. Results reported in Table 2.7 shows that the coefficients of interest (EarlyMarriage*Post) continue to be significant and similar to those in Table 2.4.

Table 2.7: Robustness Check: Sample with only married women

Variables	OLS			Fixed effects			Matching and FE		
	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early marriage	-0.250	-0.007	-0.018						
	(0.349)	(0.029)	(0.013)						
Post treatment	2.833***	0.155***	0.050***	1.975*	0.077	0.028	6.993**	0.206	-0.188
	(0.122)	(0.010)	(0.006)	(1.122)	(0.094)	(0.051)	(3.522)	(0.355)	(0.161)
EarlyMarriage*Post	0.865*	0.065	0.047*	1.118**	0.102**	0.056*	2.395**	0.196**	0.114**
	(0.513)	(0.046)	(0.027)	(0.563)	(0.051)	(0.031)	(1.086)	(0.091)	(0.056)
Other covariates		Yes			Yes			Yes	
Province FE		Yes			Yes			Yes	
Individual FE		No			Yes			Yes	
R-squared	0.224	0.138	0.067	0.264	0.153	0.065	0.303	0.207	0.140
Observations	6,927	6,927	6,927	6,927	6,927	6,927	2,131	2,131	2,131
No. of individuals	3,504	3,504	3,504	3,504	3,504	3,504	1,078	1,078	1,078

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. See Table A11 for comprehensive results.

2.7.3 Relaxing Age and Marital Status Restrictions

Another concern is that we use a restricted sample on age and marital status to estimate the effect of early marriage. Though the purpose of such restriction is to ensure a homogenous sample, as a robustness check, we relax these restrictions to examine whether the above sample selection drives the results.[21]

First, we include the group of women who are married but either separated, divorced or widowed and re-estimate the effect of early marriage on mental health. Since such changes in marital status could inevitably have a negative impact on mental health, we control for it by including a dummy variable which is assigned a value of 1 if a woman is either separated, divorced or widowed and zero otherwise. As presented in Table 2.8, the estimates are similar in magnitude to original fixed effects estimates reported in Table 2.3.

Second, we relax the age restriction and consider two alternative samples of women; (1) full sample where the maximum age is 94 years in wave 4; (2) alternative sample with a maximum age of 50 years in wave 4 which represents 85 per cent of the total sample. The results reported in Table 2.8 depicts that both the magnitude and statistical significance of our estimates are similar in both samples.

[21] These results are derived using the fixed effects estimation. The use of DD estimation also provides qualitatively similar results.

Table 2.8: Robustness check: Relaxing marital status and age restrictions

	Marital Status			Age restriction					
				Full Sample			Alternative Sample		
Variables	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early marriage	0.913*	0.087*	0.061**	1.198**	0.089*	0.053*	1.277**	0.097**	0.060**
	(0.513)	(0.046)	(0.028)	(0.510)	(0.047)	(0.028)	(0.516)	(0.047)	(0.028)
R-squared	0.278	0.162	0.068	0.265	0.151	0.065	0.271	0.156	0.068
Observations	11,386	11,386	11,386	18,861	18,861	18,861	16,219	16,219	16,219
No of individuals	5,765	5,765	5,765	9,550	9,550	9,550	8,207	8,207	8,207
Other covariates		Yes			Yes			Yes	
Province FE		Yes			Yes			Yes	
Year FE		Yes			Yes			Yes	
Individual FE		Yes			Yes			Yes	

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. See Table A12 for comprehensive results.

2.7.4 Testing Model Robustness

In identifying the causal effect, the appropriate selection of controls is essential. This is because the inclusion of too many or few number of covariates can either result in ‘bad controls’ (Angrist & Pischke, 2009) or omitted variable bias leading to endogeneity. A common approach applied in empirical work is to examine the sensitivity of treatment effects to the inclusion of observed controls (Oster, 2019). Therefore, we re-estimate the fixed effects model (in Section 2.5.1) by progressively including the control variables. Table 2.9 presents the results. The effect of early marriage on mental health remains consistently positive and significant in all specifications. Column 1 reports the estimation results with only individual fixed effects.[22] Controlling for demographics and proxies for poverty makes the effect even stronger in magnitude (Columns 3 and 4). The last column (Column 6) provides the estimates from the original specification with all covariates, as reported in Table 2.3. The stability of the early marriage coefficient suggests that our results are robust to the choice of control variables.

[22]In addition to our main variable of interest - early marriage - we also include the indicator variable which takes on a value of 1 if the woman is married and 0 otherwise, to distinguish between women who marry late and unmarried.

Table 2.9: Robustness check: Different model specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - CES-D score						
Early marriage	1.048**	1.040**	1.414***	1.437***	1.238**	1.211**
	(0.500)	(0.500)	(0.532)	(0.534)	(0.524)	(0.527)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Province FE	No	Yes	Yes	Yes	Yes	Yes
Demographic controls	No	No	Yes	Yes	Yes	Yes
Poverty controls	No	No	No	Yes	Yes	Yes
Physical health controls	No	No	No	No	Yes	Yes
Parents' mental health controls	No	No	No	No	No	Yes
R-squared	0.028	0.231	0.236	0.238	0.276	0.278
Observations	11,358	11,358	11,242	11,215	11,211	11,211
Number of individuals	5,679	5,679	5,675	5,675	5,675	5,675
Panel B - Depression						
Early marriage	0.079*	0.079*	0.117**	0.120**	0.107**	0.106**
	(0.045)	(0.045)	(0.048)	(0.048)	(0.048)	(0.048)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Province FE	No	Yes	Yes	Yes	Yes	Yes
Demographic controls	No	No	Yes	Yes	Yes	Yes
Poverty controls	No	No	No	Yes	Yes	Yes
Physical health controls	No	No	No	No	Yes	Yes
Parents' mental health controls	No	No	No	No	No	Yes
R-squared	0.017	0.127	0.132	0.134	0.159	0.161
Observations	11,358	11,358	11,242	11,215	11,211	11,211
Number of individuals	5,679	5,679	5,675	5,675	5,675	5,675
Panel C - Severe depression						
Early marriage	0.049*	0.049*	0.074***	0.076***	0.069**	0.068**
	(0.026)	(0.026)	(0.029)	(0.029)	(0.029)	(0.029)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Province FE	No	Yes	Yes	Yes	Yes	Yes
Demographic controls	No	No	Yes	Yes	Yes	Yes
Poverty controls	No	No	No	Yes	Yes	Yes
Physical health controls	No	No	No	No	Yes	Yes
Parents' mental health controls	No	No	No	No	No	Yes
R-squared	0.007	0.047	0.051	0.052	0.067	0.068
Observations	11,358	11,358	11,242	11,215	11,211	11,211
Number of individuals	5,679	5,679	5,675	5,675	5,675	5,675

Robust standard errors in parentheses, clustered at individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

One limitation of the above approach is that its validity depends only if selection on observables is informative about selection on unobservables (Oster, 2019) which may not hold in our study. Oster (2019) proposes an alternative approach to evaluate model robustness in such instances. The underlying mechanism of this methodology is to estimate a bias-adjusted treatment effect ($\tilde{\beta}$) while calculating the degree of proportionality between the observed and unobserved variables denoted as delta (δ). Table 2.10 presents the results. In all three estimations, the delta is less than one (*i.e.* $\delta \prec 1$). This indicates that the omitted variables are less influential in explaining the effect of early marriage on mental health than the included controls. We also calculate the bias-adjusted effects ($\tilde{\beta}$) which are quite similar in magnitude to controlled effects (β), implying that our estimated models are robust to omitted variable bias.

Table 2.10: Robustness check: Unobservable selection

	Baseline effects ($\dot{\beta}$) (Std. error), [R^2]	Controlled effects (β) (Std. error), [R^2]	Delta (δ)	Bias-adjusted effects ($\tilde{\beta}$)
Mental Health Score	3.13 (0.467) [0.007]	1.21 (0.527) [0.278]	0.158	0.014
Depression	0.206 (0.042) [0.005]	0.106 (0.048) [0.161]	0.126	0.070
Severe Depression	0.094 (0.025) [0.003]	0.068 (0.029) [0.068]	0.082	0.044

Both baseline and controlled effects are estimated using FE regressions with no controls and with controls respectively. We use the STATA code *psacalc* to compute delta. Bias-adjusted effects are estimated by considering the omitted variable bias.

2.7.5 Matching with More Variables

In section 2.6.2, we matched the treatment group (i.e. those who had an early marriage) and control group based on a limited number of covariates - age, quadratic of age and religion - as suggested by an OLS regression. However, it can be argued that the decision to marry early also depends on other factors such as household income, education level and physical health status of the woman. Therefore, based on our intuition, we increase the number of covariates that are used to match the treatment and control groups as a robustness check. Considering the combination that gives the best matching outcomes, the selected covariates are; age, religion, whether the woman is still schooling, level of education, the number of acute morbidities experienced during the last four weeks as a proxy for physical health, and whether the household uses the nearby river, land or sea as the toilet and residence (urban or rural) as poverty proxies. The coarsened exact matching summaries presented in Tables A14 and A15 in Appendix show that CEM has produced a reasonable match where both the overall multivariate and univariate imbalances are reduced substantially post-match. Table 2.11 reports the DD estimates with the CEM weights. The coefficients of the treatment effect (i.e. EarlyMarriage*Post) are larger in magnitude compared to matched DD estimates reported in Table 2.4 (Columns 7, 8 and 9). This is because matching on more observable characteristics results in a better counterfactual leading to strong significant results. Given that we are unable to match on all observables, this implies that our estimated results may be biased downwards.

Table 2.11: Robustness check: Alternative matching

Variables	CES-D score	Depression	Severe depression
	(1)	(2)	(3)
Post treatment	1.870	0.142	0.020
	(4.007)	(0.345)	(0.146)
EarlyMarriage*Post	4.316***	0.283**	0.161**
	(1.299)	(0.116)	(0.080)
R-squared	0.340	0.245	0.152
Observations	1,186	1,186	1,186
No of individuals	602	602	602
Other covariates		Yes	
Province FE		Yes	
Individual FE		Yes	

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. See Table A13 for comprehensive results.

2.7.6 Use of Age at Marriage to Denote Early Marriage

The main empirical results discussed in Section 2.6 are estimated by a dummy variable which takes on the value of 1 if the woman is married by the age of 18 years and 0 otherwise. As a robustness check, we further examine the consistency of our results taking age at marriage instead of the dummy variable.[23] In this regard, we employ

[23] This robustness check is based on the sample of married women since age at marriage is available only for them.

correlated random effects (CRE) model and Hausman-Taylor (HT) approach, which are explained below.

2.7.6.1 Correlated Random Effects (CRE) Model

To check the sensitivity of our results, we estimate the following alternative equation:

$$MH_{it} = \alpha + \delta AgeMarried_i + \eta \mathbf{X}_{it}^{'} + \varphi_i + \varepsilon_{it} \tag{5}$$

where MH_{it} is the mental health status (either CES-score or indicator variables as described above) of woman i in year t. $AgeMarried$ represents woman's age at marriage. $\mathbf{X}_{it}$ is the vector of covariates representing demographics, work status, education, poverty and health status of woman i in year t (same as in equation (1)). φ_i denotes unobserved individual heterogeneity and ε_{it} is the error term.

The use of fixed effects model to estimate equation (5) is not feasible as it does not permit estimating the coefficient of $AgeMarried$ (δ). This is because woman's age at marriage is a time-invariant variable. Therefore, to estimate time-invariant covariates while allowing for individual heterogeneity, we apply the correlated random effects (CRE) model. This was introduced by Mundlak (1978) and further extended by Chamberlain (1982).

Given equation (5), the individual heterogeneity term φ_i can be decomposed as:

$$\varphi_i = \psi + \xi \bar{\mathbf{X}}_i + \omega_i \tag{6}$$

where $\bar{\mathbf{X}}_i = T^{-1} \sum_{t=1}^{T} X_{it}$. By substituting equation (6), equation (5) can be rewritten as:

$$MH_{it} = \alpha + \delta AgeMarried_i + \eta \mathbf{X}_{it}^{'} + \psi + \xi \bar{\mathbf{X}}_i + \omega_i + \varepsilon_{it} \tag{7}$$

$$MH_{it} \equiv \alpha + \delta AgeMarried_i + \eta \mathbf{X}_{it}^{'} + \psi + \xi \bar{\mathbf{X}}_i + v_{it} \tag{8}$$

By assumption, $E\left(\omega_i|\mathbf{X}_i\right)$=0 and $E\left(\varepsilon_{it}|\mathbf{X}_i\right)$=0, $t = 1, ...T$ which leads to $E\left(v_{it}|\mathbf{X}_i\right)$=0. This means we can use pooled ordinary least squares (OLS) to consistently estimate all parameters of equation (8) including both time-variant and time-invariant coefficients while accounting for individual heterogeneity (Wooldridge, 2010).

2.7.6.2 Hausman-Taylor Estimation

Hausman-Taylor (HT) approach is an alternative technique to obtain estimates of both time-variant and time-invariant variables covariates. According to Hausman and Taylor (1981), it is possible to consistently and efficiently estimate the coefficients of interest, provided that specific time-varying coefficients are uncorrelated with the unobserved heterogeneity. Using the means of such time-varying covariates as instruments, unbiased estimates of time-invariant variables are obtained, whereas standard fixed effects estimation is used to estimate the time-varying variable coefficients consistently.

Following Cameron and Trivedi (2009), the individual effects model is written as:

$$MH_{it} = \alpha + \beta_1 \mathbf{X}_{1it}^{'} + \beta_2 \mathbf{X}_{2it}^{'} + \gamma_1 \mathbf{W}_{1i}^{'} + \gamma_2 AgeMarried_{2i} + \varphi_i + \varepsilon_{it} \tag{9}$$

where regressors with subscript 1 are uncorrelated with φ_i, and regressors with subscript 2 are correlated with φ_i. $\mathbf{X}$ denotes the vector of time varying regressors whereas $\mathbf{W}$ and $AgeMarried$ are the time-invariant covariates of our model.

The HT method uses random-effects transformation to derive:

$$\tilde{MH}_{it} = \beta_1 \tilde{\mathbf{X}}_{1it}^{'} + \beta_2 \tilde{\mathbf{X}}_{2it}^{'} + \gamma_1 \tilde{\mathbf{W}}_{1i}^{'} + \gamma_2 Age\tilde{M}arried_{2i} + \tilde{\varphi}_i + \tilde{\varepsilon}_{it} \tag{10}$$

where, for example, $\tilde{X}_{1it} = X_{1it} - \hat{\theta}_i \bar{X}_{1i}$

Instead of within transformation, random-effects transformation is used so that γ_1 and γ_2 can be estimated. However, $\tilde{\varphi}_i = \varphi_i \left(1 - \hat{\theta}_i\right) = 0$, suggesting the presence of fixed effects and its correlation with $\tilde{X}_{2it}$ and $Age\tilde{M}arried_{2i}$. An instrumental variable (IV) approach is used to deal with such correlation. One advantage of HT method is that, rather than using external instruments, it uses several instruments that are derived from within the model, such as: (i) for $\tilde{X}_{2it}$, the instrument used is $\ddot{X}_{2it} = X_{2it} - \bar{X}_{2i}$, which is shown to be uncorrelated with φ_i, (ii) for $Age\tilde{M}arried_{2i}$, the instrument is $\bar{X}_{1i}$, meaning it is necessary to have an equal number of time-varying exogenous regressors and time-invariant endogenous regressors, and (iii) $\ddot{X}_{1it}$ and W_{1i} are used as instruments for $\tilde{X}_{1it}$ and $\tilde{W}_{1i}$ respectively.

To ensure a consistent HT estimator two conditions should be satisfied; (1) no correlation between all regressors and the idiosyncratic error ε_{it} and (2) no correlation between the specified subset of the regressors and the fixed effect φ_i.

2.7.6.3 Estimation Results from Correlated Random Effects and Hausman-Taylor Models

Table 2.12 reports the results from correlated random effects (CRE) and Hausman-Taylor estimations. These estimates are not directly comparable to those obtained from the fixed effects estimations reported in Table 2.3, due to differences in samples. Both married and unmarried women are included in the sample used in basic fixed effects regressions, whereas only married women are included in the sample used for CRE and Hausman-Taylor regressions. This is inevitable because the age at marriage is available only for married women.

Based on CRE estimates (see Columns 1, 2 and 3) a one-year delay in marriage decreases the CES-D score by 0.03 points and the probability of having severe depression by 0.002 percentage points. Considering the sample means of mental health score (4.90) and severe depression (0.04), these estimates translate into 0.6 and five per cent decrease respectively. This is consistent with fixed effects estimates in Table 2.3, given that early marriage is likely to increase the probability of having depression. When we look at the Hausman-Taylor estimates (Columns 4, 5 and 6) the age at marriage does not have a significant effect on either the mental health score (CES-D) or severe depression. However, increasing the age at marriage by one year decreases the probability of depression by approximately three percentage points. The magnitude of the coefficients of Hausman-Taylor estimations is larger than that of CRE since Hausman-Taylor is an IV estimator.

To have a consistent Hausman-Taylor estimator, all regressors should be uncorrelated with the idiosyncratic error, and the specified subset of the regressors should be uncorrelated with the fixed effect. We test this strong assumption using Sargan-Hansen statistic. The test results are presented in Table 2.12. The p-values suggest that we cannot reject the null of valid excluded IVs indicating that the estimated model is correctly specified.

Table 2.12: Robustness check: Effect of age at marriage on mental health

Variables	CRE			HT		
	CES-D score	Depression	Severe depression	CES-D score	Depression	Severe depression
	(1)	(2)	(3)	(4)	(5)	(6)
Age married	-0.028*	-0.002	-0.002**	-0.267	-0.026*	-0.004
	(0.015)	(0.001)	(0.001)	(0.170)	(0.014)	(0.009)
Observations	9,021	9,021	9,021	9,021	9,021	9,021
No of individuals	5,118	5,118	5,118	5,118	5,118	5,118
Sargan-Hansen statistic				14.184	16.642	14.142
p-value				0.361	0.2162	0.3639

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05 * p<0.1. Age at marriage is denoted as a continuous variable. All estimations include year and province fixed effects as well as the full set of control variables. See Table A16 for comprehensive results.

2.8 Discussion

2.8.1 Interpretation of Results

Our empirical findings suggest that early marriage has negative repercussions for women's mental health. Women who marry early are more likely to have depressive or severe depressive symptoms. Departing from previous studies, we apply several estimation strategies – fixed effects, matched DD and instrumental variable framework to identify the causal relationship between early marriage and mental health. Both fixed-effects and matched DD provide a similar conclusion that early marriages have an adverse effect on women's mental health. However, we do not find any significant results using the IV approach, which merits further discussion.

Instrumental variable estimates are generally referred to as local average treatment effects (LATE). That is, it captures the effect of early marriage for the subgroup of women whose decision to marry is affected by her age at menarche – also called as compliers (Angrist & Pischke, 2009). It is possible that the causal effect for these compliers to be lower than those for the group as a whole. In other words, it cannot draw valid inferences on those women whose decision to marry is not affected by the age at menarche.[24]

The LATE interpretation of IV estimates is based on exclusion restriction, which is one of the underlying assumptions of a valid instrument. In other words, this interpretation may not hold if there is a possible violation of exclusion restriction leading to biased estimates. The exclusion restriction assumption implies that age at menarche does not affect the decision to marry early among the always-takers (women who will marry early irrespective of the age at menarche) and never-takers (women who will not marry early even with a lower age at menarche) and thus has no effect on their mental health (Jones, 2015). This means the differences in mental health status between those women who had a delayed menarche and those who had not, are driven mainly by the group of compliers. However, this may not be true. Both earlier and delayed menarche are said to be associated with depressive symptoms among girls (Mendle et al., 2016; Mendle et al., 2018; Rudolph et al., 2014). This means it is possible that the timing of puberty can affect the mental health of girls who are identified as either always-takers or never takers, which will also be captured by the IV estimates leading to imprecise estimates. Therefore, to examine whether our IV satisfies this important assumption of exclusion restriction, we follow the 'plausibly exogenous' technique proposed by Conley, Hansen and Rossi (2012).

Given that our IV model,

$$MH_i = \alpha + \beta EM_i + \eta \mathbf{X}_i^{'} + \gamma AgeMenarche_i + \varepsilon_i \tag{11}$$

The IV exclusion restriction holds if $\gamma = 0$. The notion of plausible exogeneity relaxes this condition with the assumption that it is not exactly zero but almost zero. The inference method of β depends on the various forms that γ can take; either the support of γ can be assumed or distributional assumptions of γ can be made. In this study, we consider the union of confidence interval (UCI) approach which is based on the specification of a

[24] According to Angrist and Pischke (2009), IV is not informative for always-takers and never-takers since the treatment status for these groups is unchanged by the instrument.

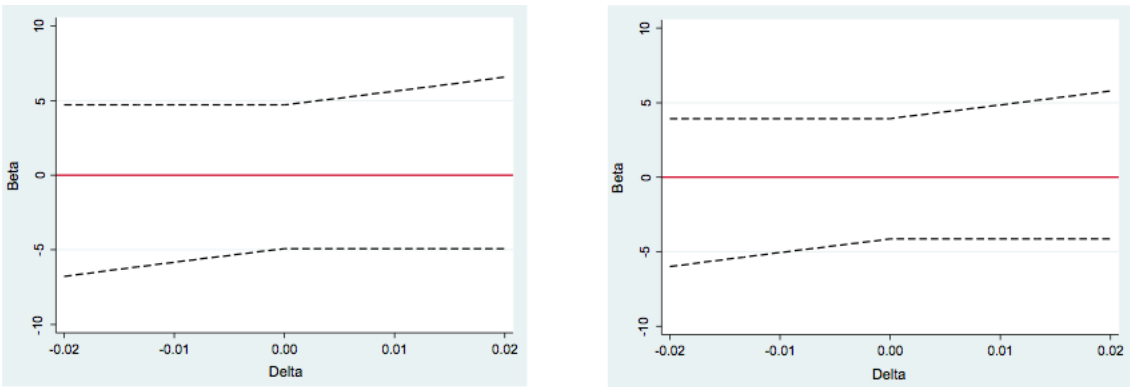
maximum and minimum prior for γ. In other words, this method takes the support of γ to be an interval $[-\delta, \delta]$ and plot a confidence interval of β versus many different values of δ (Conley et al., 2012).

The timing of puberty can either have a positive or negative effect on women's mental health, therefore we consider [-0.02, 0.02] as the possible range that γ could take. This range is based on an OLS estimation of equation (11). Figures 2.4 to 2.6 present the graphical results considering both 95% and 90% confidence bounds for the coefficient of early marriage.[25] Figure 2.4 shows that there is a substantial violation of the exclusion restriction with large confidence levels. These results are consistent even if we consider the two indicator variables for depression and severe depression (see Figures 2.5 and 2.6). This provides evidence that the age at menarche is not a valid instrument in our study context, thus leading to biased estimates.

Figure 2.4: Conley Bounds Test for Instrument Validity: Mental Health Score

Panel A: 95% Interval Estimates

Panel B: 90% Interval Estimates



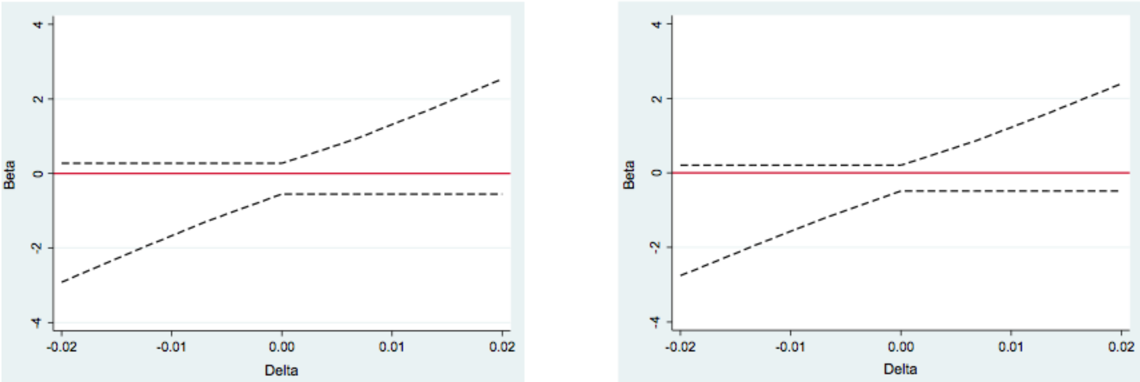
Note: Panels A and B present 95% and 90% confidence intervals respectively for the estimated coefficient of early marriage under the assumption that the age at menarche (IV) has a baseline impact on mental health score.

[25] We use the STATA command plausexog by Clarke (2017)

Figure 2.5: Conley Bounds Test for Instrument Validity: Depression

Panel A: 95% Interval Estimates

Panel B: 90% Interval Estimates

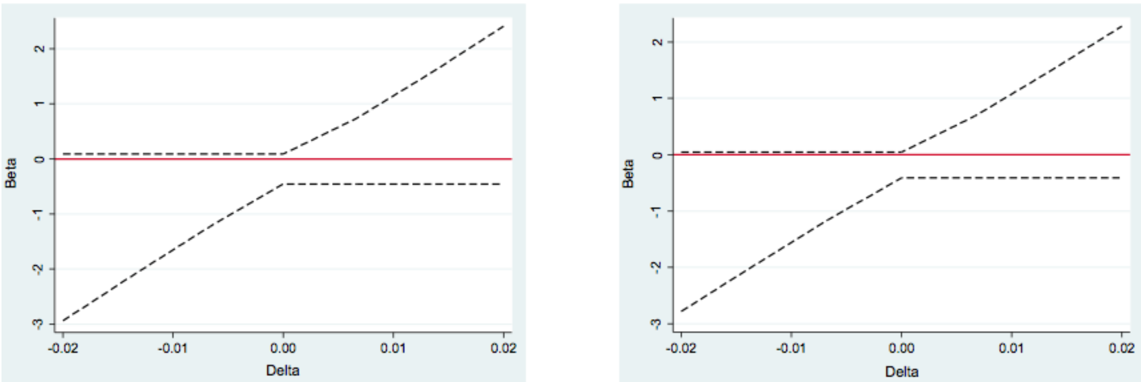


Note: Panels A and B present 95% and 90% confidence intervals respectively for the estimated coefficient of early marriage under the assumption that the age at menarche (IV) has a baseline impact on depression.

Figure 2.6: Conley Bounds Test for Instrument Validity: Severe Depression

Panel A: 95% Interval Estimates

Panel B: 90% Interval Estimates



Note: Panels A and B present 95% and 90% confidence intervals respectively for the estimated coefficient of early marriage under the assumption that the age at menarche (IV) has a baseline impact on severe depression.

2.8.2 Mechanisms and Implications

The results from panel fixed effects and matched DD models suggest that early marriage has a strong causal effect on women's mental health, which are robust to several sensitivity checks. Therefore, it is noteworthy to discuss the mechanisms in which early marriage can affect the psychological and emotional wellbeing of women.

According to Holmes and Rahe (1967), life events that require drastic changes in behaviour and lifestyle to adopt are associated with greater levels of stress. Given that marriage is a major life event (Holmes & Masuda, 1973) with diverse responsibilities, adopting into it can be too demanding, especially for young girls leading to anxiety and depression.

Furthermore, an early marriage could be a traumatic experience for girls due to several reasons. For instance, they are separated from their family and friends at a very young age, making them feel socially isolated or rejected. It also causes an abrupt end of education, limiting the girl's mobility in terms of pursuing a career or developing companionships. Intimate partner violence, forced sexual relations and early pregnancies are all associated with early marriages (UNICEF, 2014) exerting both physical and mental tension on girls.

Multiple studies show that being exposed to such adverse events during adolescence can have implications on both short-and long-term mental wellbeing. Frequent and/or prolonged exposure to adversity can inevitably result in toxic stress. This, in turn, could damage the structure of the developing brain leading to significant mental health disorders such as depression that may emerge quickly or years later (Franke, 2014; National Scientific Council on the Developing Child, 2012). Evidence from psychological studies suggests that adverse life events are a significant cause of developing depression (Hammen, 2005; Kendler et al., 1999; McMahon et al., 2003) notably, the first onset of depression occurs after a major stressful life event (Paykel, 2001). The negative effects of intense stressors are long-lasting (Shaw, 2003) where it is shown that children with high levels of exposure to adversity are more than four times as likely to develop a mental disorder during adulthood compared to those children who have not (McLaughlin et al., 2012). Taken together, it is apparent that the psychological stress and trauma that the child brides experience can cause persistent mental disorders. Our study provides evidence to this as early marriage, in fact, increases the risk of depressive symptoms.

The findings of our study have several important implications. First, the costs of early marriage are underestimated. This is because, in addition to adverse impacts of early marriage on physical wellbeing, our study shows that it can also have a significant effect on the emotional wellbeing of women, an aspect which has been generally overlooked. Therefore, the total benefit of eradicating this harmful practice globally would be much higher than the previously estimated $22 billion[26], if we consider the large economic costs of mental disorders in developing countries (Mathers et al., 2008).

[26] As cited in The Economist (26 September 2019). Retrieved from https://www.economist.com/graphic-detail/2019/09/26/indonesia-has-banned-marriage-for-young-girls

Second, our findings shed further light on the phenomenon of 'missing women' in developing countries (Anderson & Ray, 2010; Klasen & Wink, 2002; Sen, 1990). Early marriage is a manifestation of gender discrimination which disproportionately affects women. Our study highlights that such underage unions can exacerbate mental health problems such as depression and severe stress. This, in turn, can lead to detrimental consequences as individuals with mental disorders are more vulnerable to risk-taking behaviours such as self-harm. According to WHO (2018), self-harm is the second leading cause of death among girls aged 15-19 years.[27] This emphasizes the importance of ensuring psychological wellbeing among adolescent girls by protecting them from harmful practices such as early marriage. When considering the estimates of missing women, Indonesia is identified as one of the Asian countries with a significant number of missing females accounting for more than one million in 2010 (Bongaarts and Guilmoto, 2015). Moreover, according to Anderson and Ray (2010), self-inflicted injuries are a primary cause of death for over 100,000 women in East Asia. Given that early marriage is associated with poor mental health, our findings provide a possible explanation of this excess mortality of women in developing countries. Therefore, our results highlight the importance of eliminating early marriage to ensure both the short- and long-term wellbeing of women.

2.9 Conclusion

Early marriage signifies entrenched gender inequality and discrimination against girls. This inevitably leads to repercussions on the wellbeing of girls in terms of their physical, psychological and educational development. Though there is a limited number of studies on the causal effect of early marriage on education and physical health, there is no econometric analysis on the impact of early marriage on mental health. This study addresses this empirical gap by examining the causal effect of early marriage on the woman's mental health. To this end, we use longitudinal data from the Indonesia Family Life Survey (IFLS) and use several methodologies such as panel fixed effects, coarsened exact matching with difference-in-differences (matched DD) and instrumental variable approach to address the endogeneity bias of early marriage.

[27] As cited in World Health Organisation (26 February 2019). Retrieved from https://www.who.int/mental_health/maternal-child/child_adolescent/en/

The findings indicate that women who marry early are 10.6 percentage points more likely to be depressed and 6.8 percentage points more likely to be affected by severe depressive symptoms. By the same token, we find that a one-year delay in marriage decreases the likelihood of having severe depression by approximately five per cent. Taken together, our results indicate that early marriages lead to adverse mental health outcomes for women, an area that has been generally overlooked.

From a policy perspective, our findings highlight two key points. First, with almost 650 million girls and women around the world married as children, this study recognises a cohort of women who require adequate psychological support, mental healthcare and counseling services. Given the inter-generational transmission of poor mental health, addressing the mental health issues of such women would ensure the mental wellbeing of both women and their children. Second, our study provides valuable insights for laws and policies targeted at ending child marriages. Specifically, it gives a rationale for Indonesia's new policy of raising the minimum age at which girls can marry from 16 to 19 years - an important step towards ending early marriages in Indonesia.[28] Such policy measures would conclusively promote gender equality as well as better outcomes for women.

[28]As cited in The Economist (26 September 2019). Retrieved from https://www.economist.com/graphic-detail/2019/09/26/indonesia-has-banned-marriage-for-young-girls

Appendix A

Table A1: The 10-item Centre for Epidemiological Studies Depression Scale (CES-D) - Questionnaire

Below is a list of the ways you might have felt or behaved. Please tell me how often you have felt this way during the past week

		During the past week			
		Rarely or none of the time (less than 1 day)	Some or little of the time (1 - 2 days)	Occasionally or a moderate amount of time (3 - 4 days)	Most or all of the time (5 to 7 days)
1.	I was bothered by things that usually don't bother me				
2.	I had trouble concentrating in what I was doing				
3.	I felt depressed				
4.	I felt everything I did was an effort				
5.	I felt hopeful about the future				
6.	I felt fearful				
7.	My sleep was restless				
8.	I was happy				
9.	I felt lonely				
10	I could not get going				

Scoring: Zero for answers in the first column, 1 for answers in the second column, 2 for answers on the third column and 3 for answers in the fourth column. The scores of questions 5 and 8 are reversed (i.e. 3, 2, 1 and 0 respectively)

Table A2: Variable Description

Variables	Description
Mental health score	The mental health score based on CES-D-10 scale
Depression	= 1 if the CES-D score is greater than 10
Severe depression	=1 if the CES-D score is greater than 15
Early marriage	=1 if married by the age of 18 years
Demographics	
Age	Age of the individual
Height (cm)	The height in centimeters
Religion	=1 if the religion is Islam
Urban	=1 if the household is in an urban area
Married	=1 if married or cohabiting
Years married	Number of years since marriage
Mother's mental health	Mother's mental health score based on CES-D 10 scale
Father's mental health	Father's mental health score based on CES-D 10 scale
Work Status	
Employed	=1 if working/helping to get an income
Unemployed	=1 if looking for a job or unemployed
Schooling	=1 if a student
House keeping	=1 if a house keeper
Retired or sick*	=1 if retired, sick or disable
Education	
Education elementary	=1 if the individual has elementary education
Education junior	=1 if the individual has junior education
Education senior	=1 if the individual has senior education
Education tertiary	=1 if the individual has tertiary education
Education none*	=1 if the individual has no/not yet in school
Proxies for contemporaneous income	
lnpce	Logarithm of monthly per capita expenditure in 2014
HH size	The number of household members
Toilet river/land/sea	=1 if the household does not have proper toilet facilities in 2014
Cook firewood	=1 if the household uses firewood as the main source of energy for cooking in 2014
Physical health status	
Acute morbidity	Number of acute morbidities experienced during the last 4 weeks
Self reported health status	=1 if the reported health status is 'healthy'
Days missed	Number of days missed during the last 4 weeks in primary activity due to poor health
Bedridden	=1 if confined to bed or home for one or more months
Provincial Dummies	Seperate indicator variables for each of the following provinces: North Sumarta, West Sumarta, South Sumarta, Lampung, Jakarta, West Java, Central Java, Yogyakarta, East Java, Bali, West Nusa Tenggara, South Sulawesi and South Kalimantan

Variables marked with * indicate the reference group.

Table A3.1: Summary Statistics

Variable	Full		Treated		Control		Mean
	Mean	SD	Mean	SD	Mean	SD	Difference
Mental health score	4.90	4.41	4.90	4.42	4.89	4.40	0.01
Depression	0.15	0.35	0.15	0.35	0.15	0.35	0.00
Severe depression	0.04	0.21	0.05	0.22	0.04	0.20	0.01
Demographics							
Age	28.54	6.62	29.17	6.16	28.27	6.79	0.90***
Height (cm)	151.58	5.64	151.35	5.41	151.68	5.74	-0.33***
Religion - Islam	0.91	0.28	0.94	0.24	0.90	0.30	0.04***
Urban	0.56	0.50	0.40	0.49	0.63	0.48	-0.23***
Married	0.80	0.40	1.00	0.00	0.72	0.45	0.28***
No. of years married	7.42	6.54	11.93	6.44	5.49	5.56	6.44***
Mother's mental health	0.95	2.63	0.41	1.86	1.18	2.86	-0.77***
Father's mental health	0.61	1.97	0.25	1.36	0.76	2.17	-0.52***
Work Status							
Employed	0.41	0.49	0.38	0.48	0.42	0.49	-0.04***
Unemployed	0.03	0.17	0.01	0.07	0.04	0.20	-0.04***
Schooling	0.07	0.26	0.00	0.05	0.10	0.30	-0.10***
House keeping	0.49	0.50	0.61	0.49	0.44	0.50	0.17***
Retired or sick	0.00	0.04	0.00	0.05	0.00	0.04	0.00
Education							
Education none	0.01	0.09	0.02	0.13	0.00	0.07	0.01
Education elementary	0.25	0.43	0.45	0.50	0.16	0.36	0.30***
Education junior	0.24	0.43	0.34	0.48	0.20	0.40	0.15***
Education senior	0.35	0.48	0.17	0.37	0.43	0.50	-0.26***
Education tertiary	0.15	0.36	0.02	0.12	0.21	0.40	-0.19***
Poverty							
HH size	4.39	1.80	4.43	1.57	4.38	1.89	0.06
lnpce	13.33	0.89	13.17	0.83	13.40	0.91	-0.22***
Toilet river/land/sea	0.11	0.31	0.17	0.37	0.08	0.28	0.08***
Cook firewood	0.25	0.43	0.34	0.47	0.21	0.41	0.13***
Physical health status							
Acute morbidity	2.65	2.13	2.58	2.16	2.68	2.11	-0.11**
Health Status	0.84	0.36	0.83	0.37	0.85	0.36	-0.01*
Days missed	1.77	3.65	1.76	3.73	1.77	3.61	-0.02
Bed ridden	0.26	1.23	0.27	1.23	0.25	1.23	0.01
Instrument							
Age at menarche	13.64	1.54	13.61	1.58	13.65	1.52	-0.04

Notes: Mean difference is the difference of means between child brides and non-child brides for each of the variables. *** p<0.01, ** p<0.05, * p<0.1.

Table A3.2: Sample Means by Waves

Variable	Full		Treated		Control	
	Wave 4 (2007)	Wave 5 (2014)	Wave 4 (2007)	Wave 5 (2014)	Wave 4 (2007)	Wave 5 (2014)
Mental health score	3.45	6.34	3.22	6.44	3.54	6.30
Depression	0.06	0.23	0.05	0.24	0.07	0.23
Severe depression	0.01	0.08	0.01	0.08	0.02	0.07
Demographics						
Age	25.13	31.96	26.01	32.06	24.78	31.91
Height (cm)	151.39	151.77	151.18	151.51	151.48	151.90
Religion - Islam	0.91	0.91	0.94	0.94	0.90	0.90
Urban	0.52	0.60	0.35	0.45	0.60	0.67
Married	0.70	0.90	1.00	1.00	0.58	0.86
No. of years married	4.67	10.18	8.81	14.78	3.01	8.07
Mother's mental health	0.97	0.93	0.34	0.48	1.23	1.14
Father's mental health	0.66	0.55	0.20	0.29	0.84	0.68
Work status						
Employed	0.36	0.45	0.35	0.40	0.37	0.47
Unemployed	0.05	0.01	0.01	0.00	0.06	0.02
Schooling	0.13	0.01	0.00	0.00	0.18	0.01
House keeping	0.46	0.52	0.64	0.59	0.39	0.49
Retired or sick	0.01	0.01	0.02	0.02	0.00	0.01
Education						
Education none	0.01	0.01	0.02	0.02	0.00	0.01
Education elementary	0.25	0.24	0.48	0.43	0.16	0.15
Education junior	0.25	0.24	0.34	0.35	0.21	0.19
Education senior	0.37	0.33	0.15	0.18	0.46	0.40
Education tertiary	0.12	0.18	0.01	0.02	0.16	0.25
Poverty						
HH size	4.39	4.40	4.37	4.49	4.40	4.36
lnpce	12.96	13.69	12.74	13.57	13.05	13.75
Toilet river/land/sea	0.15	0.07	0.24	0.10	0.12	0.05
Cook firewood	0.34	0.16	0.47	0.22	0.29	0.13
Physical health status						
Acute morbidity	2.33	2.97	2.25	2.88	2.36	3.02
Health status	0.89	0.80	0.89	0.78	0.88	0.81
Days missed	1.57	1.97	1.44	2.04	1.61	1.94
Bed ridden	0.23	0.29	0.20	0.33	0.24	0.27
Instrument						
Age at menarche	13.64	13.64	13.62	13.60	13.64	13.66

Table A4: OLS, RE and FE estimation results

Variables	OLS			Random effects			Fixed effects		
	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early marriage	-0.038	-0.000	0.006	-0.019	0.001	0.006	1.211**	0.106**	0.068**
	(0.125)	(0.010)	(0.007)	(0.125)	(0.010)	(0.007)	(0.527)	(0.048)	(0.029)
Demographics									
Religion	-0.496***	-0.020	-0.027**	-0.499***	-0.020	-0.027**			
	(0.182)	(0.015)	(0.010)	(0.182)	(0.015)	(0.010)			
Age	0.080	0.003	0.003	0.084	0.003	0.003	0.295**	0.028**	0.007
	(0.053)	(0.004)	(0.003)	(0.053)	(0.004)	(0.003)	(0.147)	(0.012)	(0.008)
Age2	-0.002**	-0.000	-0.000	-0.002**	-0.000	-0.000	-0.001	-0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Years married	0.020	0.001	-0.000	0.018	0.001	-0.000	-0.083*	-0.012***	-0.006**
	(0.016)	(0.001)	(0.001)	(0.016)	(0.001)	(0.001)	(0.046)	(0.004)	(0.003)
Married	-0.823***	-0.031**	-0.022***	-0.792***	-0.030**	-0.021**	-0.563**	-0.022	-0.013
	(0.159)	(0.013)	(0.008)	(0.158)	(0.013)	(0.008)	(0.248)	(0.021)	(0.014)
Urban	0.052	0.007	-0.007	0.045	0.007	-0.007	-0.014	0.021	-0.017*
	(0.091)	(0.008)	(0.005)	(0.091)	(0.008)	(0.005)	(0.190)	(0.017)	(0.010)
Height_cm	-0.025***	-0.002***	-0.001**	-0.025***	-0.002***	-0.001**	0.004	-0.000	-0.000
	(0.007)	(0.001)	(0.000)	(0.007)	(0.001)	(0.000)	(0.022)	(0.002)	(0.001)
Work status									
Employed	-0.913	-0.119*	-0.055	-0.835	-0.115*	-0.053	-0.174	-0.029	-0.023
	(0.827)	(0.068)	(0.064)	(0.831)	(0.069)	(0.064)	(1.145)	(0.103)	(0.072)
Unemployed	-0.825	-0.103	-0.053	-0.723	-0.098	-0.050	0.234	0.014	0.015
	(0.851)	(0.070)	(0.065)	(0.856)	(0.071)	(0.064)	(1.191)	(0.107)	(0.074)
Schooling	-0.332	-0.072	-0.039	-0.262	-0.068	-0.038	0.682	0.059	-0.001
	(0.837)	(0.069)	(0.064)	(0.843)	(0.070)	(0.064)	(1.179)	(0.107)	(0.074)
House keeping	-0.998	-0.127*	-0.055	-0.930	-0.123*	-0.054	-0.429	-0.040	-0.022
	(0.829)	(0.068)	(0.064)	(0.833)	(0.069)	(0.064)	(1.146)	(0.104)	(0.072)
Education									
Education elemen.	0.537	0.039	0.019	0.521	0.038	0.019	0.363	-0.010	0.032
	(0.355)	(0.028)	(0.018)	(0.356)	(0.029)	(0.018)	(0.804)	(0.067)	(0.048)
Education junior	0.152	0.009	0.002	0.139	0.008	0.002	0.304	-0.003	0.000
	(0.357)	(0.029)	(0.018)	(0.358)	(0.029)	(0.018)	(0.806)	(0.067)	(0.050)
Education senior	0.183	0.019	0.004	0.155	0.017	0.004	-0.057	-0.030	-0.016
	(0.358)	(0.029)	(0.018)	(0.359)	(0.029)	(0.018)	(0.848)	(0.071)	(0.052)
Education tertiary	0.175	0.017	0.003	0.146	0.016	0.003	0.175	-0.020	-0.022
	(0.372)	(0.030)	(0.019)	(0.373)	(0.030)	(0.019)	(0.886)	(0.075)	(0.056)
Poverty proxies									
lnpce	-0.130**	-0.005	0.001	-0.113**	-0.005	0.001	0.129	0.007	0.008*
	(0.054)	(0.004)	(0.003)	(0.054)	(0.004)	(0.003)	(0.083)	(0.007)	(0.004)
Toilet-river/land	0.049	-0.004	-0.003	0.053	-0.004	-0.003	0.102	0.003	0.001
	(0.121)	(0.010)	(0.006)	(0.121)	(0.010)	(0.006)	(0.204)	(0.017)	(0.011)
Cook firewood	0.070	0.005	0.001	0.053	0.004	0.000	-0.230	-0.017	-0.004
	(0.101)	(0.008)	(0.005)	(0.101)	(0.008)	(0.005)	(0.158)	(0.014)	(0.008)
Household size	-0.003	0.000	0.001	-0.005	0.000	0.001	-0.044	-0.003	-0.001
	(0.025)	(0.002)	(0.001)	(0.025)	(0.002)	(0.001)	(0.043)	(0.004)	(0.002)
Physical health									
Acute morbidity	0.442***	0.028***	0.009***	0.432***	0.028***	0.009***	0.286***	0.018***	0.006***
	(0.021)	(0.002)	(0.001)	(0.021)	(0.002)	(0.001)	(0.031)	(0.003)	(0.002)
Health status	-1.272***	-0.086***	-0.043***	-1.272***	-0.086***	-0.043***	-1.180***	-0.078***	-0.048***
	(0.134)	(0.012)	(0.008)	(0.133)	(0.012)	(0.008)	(0.168)	(0.015)	(0.010)
Days missed	0.087***	0.005***	0.003***	0.083***	0.005***	0.003***	0.042**	0.002	0.001
	(0.015)	(0.001)	(0.001)	(0.015)	(0.001)	(0.001)	(0.018)	(0.002)	(0.001)

Bed ridden	0.136***	0.012***	0.007**	0.140***	0.013***	0.007**	0.180***	0.016***	0.006*
	(0.047)	(0.004)	(0.003)	(0.046)	(0.004)	(0.003)	(0.050)	(0.004)	(0.003)
Parents' mental health									
Mother's mental	0.078***	0.004**	0.002*	0.077***	0.004**	0.002*	0.061**	0.003	0.001
health score	(0.022)	(0.002)	(0.001)	(0.021)	(0.002)	(0.001)	(0.030)	(0.003)	(0.002)
Father's mental	0.044	0.002	-0.002	0.043	0.002	-0.002	0.028	0.002	0.001
health score	(0.027)	(0.003)	(0.001)	(0.027)	(0.003)	(0.001)	(0.037)	(0.003)	(0.002)
Mother's mental	0.415**	0.025*	0.017*	0.402**	0.025*	0.016*	0.107	-0.001	0.001
health-missing	(0.171)	(0.014)	(0.009)	(0.169)	(0.014)	(0.009)	(0.275)	(0.025)	(0.014)
Father's mental	0.213	0.001	-0.005	0.174	-0.000	-0.005	-0.452	-0.047*	-0.009
health-missing	(0.183)	(0.015)	(0.009)	(0.181)	(0.015)	(0.009)	(0.279)	(0.025)	(0.015)
Constant	12.024***	0.647***	0.213**	11.721***	0.635***	0.210**	-1.985	-0.522	-0.100
	(1.737)	(0.144)	(0.097)	(1.735)	(0.144)	(0.096)	(5.671)	(0.468)	(0.287)
Observations	11,211	11,211	11,211	11,211	11,211	11,211	11,211	11,211	11,211
R-squared	0.228	0.138	0.063				0.278	0.161	0.068
No. of individuals				5,675	5,675	5,675	5,675	5,675	5,675

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. Early marriage is denoted as a binary variable which takes on a value of 1 if the woman is married by the age of 18 years or 0 otherwise. All estimations include province and year fixed effects. Dep. denotes depression.

Table A5: Difference-in-Differences Estimates

Variables	OLS			DID			Matching DID		
	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early marriage	-0.042	0.006	-0.013						
(treated)	(0.324)	(0.028)	(0.012)						
Post treatment	2.839***	0.163***	0.053***	1.788*	0.047	0.011	1.210	-0.104	-0.126
	(0.113)	(0.010)	(0.006)	(1.038)	(0.089)	(0.050)	(2.584)	(0.253)	(0.135)
EarlyMarriage*Post	0.730	0.057	0.046*	1.160**	0.096**	0.062**	2.625***	0.190**	0.117**
	(0.500)	(0.045)	(0.027)	(0.533)	(0.049)	(0.029)	(0.884)	(0.077)	(0.048)
Demographics									
Religion	-0.387*	-0.013	-0.020*						
	(0.201)	(0.016)	(0.011)						
Age	0.210***	0.017***	0.009**	0.341*	0.036**	0.015	-0.207	0.023	-0.022
	(0.069)	(0.006)	(0.003)	(0.180)	(0.015)	(0.009)	(0.553)	(0.051)	(0.027)
Age2	-0.004***	-0.000***	-0.000**	-0.003	-0.000	-0.000	0.012	0.001	0.001**
	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.010)	(0.001)	(0.001)
Years married	0.035*	0.002	0.000	-0.077	-0.011***	-0.005**	-0.471**	-0.037**	-0.020**
	(0.019)	(0.002)	(0.001)	(0.049)	(0.004)	(0.003)	(0.186)	(0.016)	(0.009)
Married	-0.933***	-0.045***	-0.028***	-0.596**	-0.032	-0.020	0.713	0.047	0.004
	(0.177)	(0.015)	(0.009)	(0.261)	(0.023)	(0.014)	(0.651)	(0.056)	(0.030)
Urban	-0.002	0.000	-0.005	-0.088	0.014	-0.012	-0.523	-0.001	-0.018
	(0.109)	(0.009)	(0.006)	(0.219)	(0.019)	(0.012)	(0.494)	(0.046)	(0.030)
Height_cm	-0.024***	-0.002***	-0.001	-0.025	-0.003*	-0.002*	-0.005	-0.003	-0.001
	(0.008)	(0.001)	(0.000)	(0.023)	(0.002)	(0.001)	(0.051)	(0.005)	(0.002)
Work status									
Employed	-0.497	-0.066	-0.084	0.779	0.113	0.007	3.409	0.336	0.103
	(0.957)	(0.076)	(0.075)	(1.427)	(0.119)	(0.084)	(2.401)	(0.282)	(0.120)
Unemployed	-0.378	-0.049	-0.083	1.082	0.144	0.042	3.929	0.403	0.120
	(0.975)	(0.077)	(0.075)	(1.464)	(0.122)	(0.086)	(2.402)	(0.282)	(0.121)
Schooling	0.231	-0.000	-0.061	1.605	0.197	0.030	4.257*	0.448	0.125
	(0.961)	(0.076)	(0.074)	(1.448)	(0.121)	(0.085)	(2.313)	(0.273)	(0.117)
House keeping	-0.540	-0.067	-0.082	0.488	0.101	0.008	1.668	0.229	0.075
	(0.961)	(0.076)	(0.075)	(1.433)	(0.119)	(0.084)	(2.421)	(0.283)	(0.122)
Education									
Education elemen.	0.748	0.033	0.038*	-0.486	-0.080	-0.013	0.544	-0.251**	0.040
	(0.501)	(0.041)	(0.020)	(0.851)	(0.086)	(0.052)	(1.184)	(0.117)	(0.081)
Education junior	0.380	0.009	0.024	-0.166	-0.076	-0.042	1.332	-0.099	0.025
	(0.498)	(0.041)	(0.020)	(0.776)	(0.080)	(0.050)	(1.245)	(0.116)	(0.076)
Education senior	0.406	0.018	0.022	-0.245	-0.073	-0.053	1.771	-0.081	0.013
	(0.495)	(0.041)	(0.020)	(0.847)	(0.084)	(0.056)	(1.279)	(0.119)	(0.072)
Education tertiary	0.333	0.009	0.020	-0.212	-0.085	-0.067	1.425	-0.145	-0.004
	(0.502)	(0.041)	(0.020)	(0.889)	(0.087)	(0.060)	(1.347)	(0.125)	(0.073)
Poverty proxies									
lnpce	-0.070	-0.001	0.004	0.189*	0.010	0.009*	0.604***	0.024	0.017
	(0.064)	(0.005)	(0.003)	(0.096)	(0.008)	(0.005)	(0.223)	(0.021)	(0.012)
Toilet-river/land	0.044	-0.015	-0.005	0.172	0.016	0.012	0.415	0.018	0.006
	(0.160)	(0.013)	(0.008)	(0.269)	(0.023)	(0.013)	(0.579)	(0.051)	(0.034)
Cook firewood	0.099	0.011	0.003	-0.192	-0.007	0.005	-0.415	-0.010	-0.008
	(0.129)	(0.010)	(0.007)	(0.197)	(0.018)	(0.010)	(0.464)	(0.041)	(0.026)
Household size	-0.000	0.001	0.002	-0.030	-0.001	-0.000	0.053	0.007	0.002
	(0.029)	(0.002)	(0.002)	(0.049)	(0.004)	(0.003)	(0.114)	(0.010)	(0.006)
Physical health									
Acute morbidity	0.456***	0.029***	0.010***	0.289***	0.019***	0.006***	0.483***	0.027***	0.015***
	(0.025)	(0.002)	(0.001)	(0.036)	(0.003)	(0.002)	(0.084)	(0.008)	(0.005)

Health status	-1.428***	-0.101***	-0.050***	-1.376***	-0.094***	-0.055***	-1.808***	-0.152***	-0.074**
	(0.161)	(0.014)	(0.010)	(0.201)	(0.018)	(0.012)	(0.463)	(0.044)	(0.030)
Days missed	0.078***	0.005***	0.002*	0.034*	0.001	0.001	0.031	0.005	-0.001
	(0.017)	(0.001)	(0.001)	(0.020)	(0.002)	(0.001)	(0.065)	(0.005)	(0.003)
Bed ridden	0.149***	0.015***	0.009**	0.189***	0.019***	0.005	0.137	0.027*	-0.001
	(0.058)	(0.005)	(0.004)	(0.060)	(0.005)	(0.004)	(0.151)	(0.015)	(0.010)
Parents' mental health									
Mother's mental	0.079***	0.004**	0.003*	0.063**	0.003	0.001	0.052	0.004	-0.001
health score	(0.023)	(0.002)	(0.001)	(0.032)	(0.003)	(0.002)	(0.055)	(0.005)	(0.004)
Father's mental	0.031	0.001	-0.002	0.013	0.001	0.001	0.023	-0.000	0.003
health score	(0.027)	(0.003)	(0.001)	(0.037)	(0.003)	(0.002)	(0.055)	(0.005)	(0.003)
Mother's mental	0.410**	0.027*	0.019**	0.045	0.003	0.004	-0.015	-0.017	0.005
health-missing	(0.186)	(0.016)	(0.010)	(0.292)	(0.027)	(0.015)	(0.621)	(0.055)	(0.032)
Father's mental	0.106	-0.007	-0.006	-0.458	-0.045*	-0.002	-0.337	0.011	-0.008
health-missing	(0.193)	(0.016)	(0.010)	(0.291)	(0.027)	(0.016)	(0.525)	(0.047)	(0.026)
Constant	5.884***	0.204	0.034	-0.957	-0.305	-0.091	-8.100	-0.752	-0.244
	(2.097)	(0.173)	(0.115)	(5.811)	(0.469)	(0.277)	(11.701)	(1.016)	(0.566)
Observations	7,988	7,988	7,988	7,988	7,988	7,988	2,948	2,948	2,948
R-squared	0.228	0.142	0.066	0.274	0.162	0.069	0.318	0.212	0.110
No of individuals				4,048	4,048	4,048	1,495	1,495	1,495

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. All estimations include province and year fixed effects. Dep. denotes depression.

Table A6: Regression on Early marriage

Variables	OLS	Probit
Religion	0.029***	0.872***
	(0.009)	(0.298)
Age	-0.102***	-0.566
	(0.009)	(0.445)
Age2	0.002***	0.007
	(0.000)	(0.012)
Urban	-0.005	-0.122
	(0.007)	(0.120)
Height cm	-0.000	-0.006
	(0.001)	(0.009)
Employed	-0.063	-0.565
	(0.100)	(0.596)
Unemployed	-0.027	-0.472
	(0.102)	(0.604)
Schooling	-0.158	-1.114*
	(0.102)	(0.597)
House keeping	-0.062	-0.768
	(0.100)	(0.607)
Education element.	0.011	0.180
	(0.033)	(0.475)
Education junior	0.001	-0.066
	(0.033)	(0.466)
Education senior	-0.015	-0.135
	(0.033)	(0.467)
Education tertiary	0.006	-0.568
	(0.033)	(0.574)
lnpce	-0.001	-0.017
	(0.004)	(0.064)
Toilet-river/land	0.009	0.087
	(0.011)	(0.140)
Cook firewood	0.010	0.127
	(0.009)	(0.125)
Household size	0.000	-0.015
	(0.002)	(0.028)
Acute morbidity	0.001	0.042
	(0.002)	(0.026)
Health status	0.006	0.074
	(0.009)	(0.163)
Days missed	0.001*	0.026
	(0.001)	(0.018)
Bed ridden	-0.000	0.022
	(0.002)	(0.038)
Mother's mental	0.001	0.003
health score	(0.002)	(0.016)
Father's mental	-0.005*	-0.044*
health score	(0.003)	(0.023)
Mother's mental	0.005	-0.016
health-missing	(0.011)	(0.156)
Father's mental	-0.013	-0.179
health-missing	(0.015)	(0.148)
Constant	1.527***	7.772*
	(0.177)	(4.633)
R-squared	0.174	

Robust standard errors in parentheses, clustered at individual level.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Estimations are based on only wave 4 observations and include province and year fixed effects. N= 3988

Table A7: Coarsened Exact Matching Summary

	Control (Early marriage = 0)	Treatment (Early marriage = 1)
All	3892	160
Matched	1336	160
Unmatched	2556	0

Table A8: Covariate Balance

Pre-match multivariate L1 distance: 0.7875

	Pre-match univariate imbalance		Sample mean	
	L1	Mean Difference	Control (EM = 0)	Treatment (EM = 1)
Religion	0.067	0.067	0.898	0.963
Age	0.785	-8.710	25.123	16.413
Age2	0.769	-391.883	663.583	271.700

Post-match multivariate L1 distance: 0.000

	Post-match univariate imbalance		Sample mean	
	L1	Mean Difference	Control (EM = 0)	Treatment (EM = 1)
Religion	0.000	0.000	0.969	0.969
Age	0.000	-0.045	16.458	16.413
Age2	0.000	-1.334	273.034	271.700

Table A9: IV Estimates

Variables	2SLS			IV with RE		
	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.
	(1)	(2)	(3)	(4)	(5)	(6)
Early marriage	-0.104	-0.142	-0.184	-0.080	-0.142	-0.182
	(2.457)	(0.210)	(0.139)	(2.455)	(0.210)	(0.138)
Demographics						
Years married	0.023	0.009	0.011	0.021	0.008	0.010
	(0.132)	(0.011)	(0.007)	(0.131)	(0.011)	(0.007)
Married	-0.802***	-0.004	0.001	-0.741***	-0.001	0.006
	(0.268)	(0.022)	(0.014)	(0.283)	(0.022)	(0.016)
Religion	-0.466**	-0.018	-0.024**	-0.468**	-0.018	-0.024**
	(0.195)	(0.016)	(0.011)	(0.195)	(0.016)	(0.012)
Age	0.044	-0.011	-0.007	0.050	-0.010	-0.007
	(0.128)	(0.011)	(0.007)	(0.125)	(0.011)	(0.007)
Age2	-0.002	0.000	-0.000	-0.002*	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Urban	0.072	0.006	-0.009	0.071	0.006	-0.009
	(0.108)	(0.009)	(0.006)	(0.107)	(0.009)	(0.006)
Height_cm	-0.025***	-0.002***	-0.001**	-0.025***	-0.002***	-0.001**
	(0.007)	(0.001)	(0.000)	(0.007)	(0.001)	(0.000)
Work status						
Employed	-1.398	-0.120	-0.073	-1.354	-0.117	-0.070
	(0.945)	(0.078)	(0.074)	(0.943)	(0.079)	(0.072)
Unemployed	-1.500	-0.130	-0.078	-1.394	-0.125	-0.071
	(0.969)	(0.079)	(0.074)	(0.969)	(0.080)	(0.073)
Schooling	-0.625	-0.089	-0.096	-0.556	-0.084	-0.090
	(1.003)	(0.082)	(0.076)	(1.001)	(0.083)	(0.074)
House keeping	-1.509	-0.128	-0.072	-1.476	-0.126	-0.069
	(0.955)	(0.079)	(0.074)	(0.951)	(0.079)	(0.072)
Education						
Education elemen.	0.228	0.020	0.010	0.225	0.019	0.011
	(0.366)	(0.031)	(0.021)	(0.369)	(0.031)	(0.021)
Education junior	-0.103	-0.014	-0.016	-0.103	-0.015	-0.015
	(0.408)	(0.034)	(0.023)	(0.408)	(0.035)	(0.023)
Education senior	-0.155	-0.020	-0.030	-0.170	-0.022	-0.029
	(0.516)	(0.044)	(0.029)	(0.514)	(0.044)	(0.029)
Education tertiary	-0.142	-0.006	-0.009	-0.164	-0.008	-0.009
	(0.395)	(0.033)	(0.022)	(0.398)	(0.033)	(0.022)
Poverty proxies						
lnpce	-0.177***	-0.005	0.003	-0.163**	-0.005	0.003
	(0.066)	(0.006)	(0.003)	(0.065)	(0.006)	(0.003)
Toilet-river/land	0.025	-0.008	-0.003	0.025	-0.008	-0.003
	(0.125)	(0.010)	(0.007)	(0.126)	(0.010)	(0.007)
Cook firewood	0.044	0.002	0.003	0.027	0.001	0.002
	(0.106)	(0.009)	(0.006)	(0.105)	(0.009)	(0.006)
Household size	0.002	0.002	0.001	-0.001	0.002	0.000
	(0.027)	(0.002)	(0.001)	(0.027)	(0.002)	(0.001)
Physical health						
Acute morbidity	0.439***	0.027***	0.009***	0.428***	0.027***	0.009***
	(0.023)	(0.002)	(0.001)	(0.023)	(0.002)	(0.001)
Health status	-1.239***	-0.084***	-0.041***	-1.238***	-0.084***	-0.042***
	(0.140)	(0.012)	(0.008)	(0.140)	(0.012)	(0.008)
Days missed	0.092***	0.005***	0.003***	0.088***	0.005***	0.003***
	(0.016)	(0.001)	(0.001)	(0.016)	(0.001)	(0.001)

Bed ridden	0.120**	0.011***	0.007**	0.125**	0.012***	0.007**
	(0.050)	(0.004)	(0.003)	(0.049)	(0.004)	(0.003)
Parents' mental health						
Mother's mental	0.057**	0.001	0.001	0.058**	0.001	0.001
health score	(0.027)	(0.002)	(0.002)	(0.027)	(0.002)	(0.001)
Father's mental	0.071**	0.005	-0.001	0.070**	0.005	-0.001
health score	(0.036)	(0.003)	(0.002)	(0.036)	(0.003)	(0.002)
Mother's mental	0.302	0.013	0.012	0.302	0.013	0.010
health-missing	(0.196)	(0.016)	(0.010)	(0.193)	(0.016)	(0.010)
Father's mental	0.413*	0.016	-0.003	0.363*	0.013	-0.003
health-missing	(0.215)	(0.018)	(0.011)	(0.213)	(0.018)	(0.010)
Constant	13.759***	0.913***	0.436***	13.447***	0.898***	0.425***
	(2.856)	(0.238)	(0.164)	(2.830)	(0.237)	(0.161)
Observations	10,154	10,154	10,154	10,154	10,154	10,154
R-squared	0.226	0.125	-0.000			
No. of individuals	5,133	5,133	5,133	5,133	5,133	5,133

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. All estimations include province and year fixed effects. Dep. denotes depression.

Table A10: Placebo test with a false treatment group

Variables	OLS			Fixed effects			Matching and FE		
	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Marriage	0.948***	0.056**	0.027*				-	-	-
(false treatment)	(0.318)	(0.025)	(0.016)						
Post treatment	2.798***	0.163***	0.055***	1.980	0.038	0.024	1.808	0.027	0.021
	(0.136)	(0.012)	(0.007)	(1.249)	(0.108)	(0.059)	(1.985)	(0.175)	(0.099)
Marriage*Post	-0.812**	-0.058	-0.023	-0.657	-0.040	-0.023	-0.594	-0.043	-0.009
	(0.410)	(0.038)	(0.023)	(0.449)	(0.042)	(0.025)	(0.524)	(0.048)	(0.028)
Demographics									
Religion	-0.371*	-0.008	-0.018				-	-	-
	(0.219)	(0.017)	(0.012)						
Age	0.300***	0.024***	0.013***	0.317	0.040**	0.019*	0.425	0.048	0.005
	(0.084)	(0.007)	(0.004)	(0.218)	(0.019)	(0.011)	(0.372)	(0.032)	(0.019)
Age2	-0.006***	-0.000***	-0.000***	-0.003	-0.000	-0.000*	-0.005	-0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)
Years married	0.040	0.003	0.000	-0.065	-0.008*	-0.004	-0.068	-0.008	-0.007
	(0.025)	(0.002)	(0.001)	(0.054)	(0.005)	(0.003)	(0.084)	(0.007)	(0.004)
Married	-0.906***	-0.043***	-0.029***	-0.503*	-0.026	-0.019	-0.269	-0.011	-0.012
	(0.198)	(0.017)	(0.010)	(0.289)	(0.025)	(0.016)	(0.408)	(0.033)	(0.021)
Urban	0.011	0.002	-0.004	-0.053	0.022	-0.017	-0.357	0.023	-0.021
	(0.127)	(0.010)	(0.006)	(0.243)	(0.022)	(0.013)	(0.336)	(0.030)	(0.020)
Height cm	-0.037***	-0.003***	-0.001***	-0.021	-0.003	-0.002*	-0.022	-0.004	-0.002
	(0.009)	(0.001)	(0.000)	(0.027)	(0.002)	(0.001)	(0.038)	(0.003)	(0.002)
Work status									
Employed	-1.094	-0.118	-0.111	-0.506	-0.017	-0.035	-0.001	0.116	0.034
	(1.041)	(0.082)	(0.084)	(1.430)	(0.115)	(0.080)	(1.749)	(0.221)	(0.078)
Unemployed	-0.979	-0.095	-0.110	-0.463	-0.001	-0.011	0.429	0.172	0.059
	(1.061)	(0.083)	(0.085)	(1.471)	(0.119)	(0.081)	(1.767)	(0.223)	(0.079)
Schooling	-0.219	-0.043	-0.081	0.256	0.061	-0.004	0.927	0.206	0.057
	(1.046)	(0.083)	(0.084)	(1.453)	(0.119)	(0.080)	(1.717)	(0.221)	(0.076)
House keeping	-1.048	-0.115	-0.108	-0.730	-0.025	-0.036	-0.478	0.098	0.032
	(1.046)	(0.082)	(0.084)	(1.440)	(0.116)	(0.079)	(1.759)	(0.221)	(0.078)
Education									
Education elemen.	1.102*	0.053	0.062***	0.460	-0.041	0.084	-0.733	-0.233	0.074
	(0.580)	(0.049)	(0.011)	(1.135)	(0.120)	(0.054)	(1.209)	(0.148)	(0.058)
Education junior	0.616	0.015	0.049***	0.459	-0.078	0.034	0.225	-0.140	0.056
	(0.576)	(0.048)	(0.010)	(1.005)	(0.111)	(0.049)	(1.152)	(0.136)	(0.053)
Education senior	0.624	0.020	0.047***	0.350	-0.080	0.029	0.172	-0.147	0.032
	(0.573)	(0.048)	(0.009)	(1.080)	(0.114)	(0.055)	(1.165)	(0.134)	(0.052)
Education tertiary	0.548	0.011	0.041***	0.262	-0.100	0.006	-0.198	-0.194	0.005
	(0.582)	(0.048)	(0.010)	(1.118)	(0.117)	(0.057)	(1.212)	(0.136)	(0.053)
Poverty proxies									
lnpce	-0.047	0.001	0.005	0.251**	0.010	0.013**	0.555***	0.024*	0.022***
	(0.074)	(0.006)	(0.004)	(0.108)	(0.009)	(0.006)	(0.145)	(0.013)	(0.008)
Toilet - river/land	-0.043	-0.033**	-0.013	0.104	-0.000	-0.005	0.347	0.028	0.010
	(0.186)	(0.015)	(0.009)	(0.332)	(0.028)	(0.017)	(0.448)	(0.040)	(0.024)
Cook firewood	0.026	0.007	0.007	-0.213	-0.008	0.012	-0.106	-0.009	0.014
	(0.152)	(0.012)	(0.008)	(0.234)	(0.020)	(0.012)	(0.333)	(0.028)	(0.017)
Household size	-0.031	-0.002	0.001	-0.057	-0.006	-0.001	-0.062	-0.002	-0.002
	(0.033)	(0.003)	(0.002)	(0.056)	(0.005)	(0.003)	(0.079)	(0.007)	(0.005)
Physical health									
Acute morbidity	0.471***	0.029***	0.009***	0.276***	0.018***	0.004	0.403***	0.025***	0.009***
	(0.029)	(0.003)	(0.002)	(0.041)	(0.004)	(0.002)	(0.059)	(0.006)	(0.003)
Health status	-1.467***	-0.109***	-0.062***	-1.509***	-0.108***	-0.070***	-1.579***	-0.129***	-0.066***
	(0.183)	(0.016)	(0.011)	(0.227)	(0.020)	(0.013)	(0.338)	(0.030)	(0.021)

Days missed	0.079***	0.004***	0.002	0.032	0.000	0.001	0.006	0.001	0.000
	(0.019)	(0.002)	(0.001)	(0.024)	(0.002)	(0.002)	(0.037)	(0.003)	(0.002)
Bed ridden	0.104	0.011**	0.008**	0.197***	0.019***	0.007*	0.191*	0.024***	0.003
	(0.064)	(0.005)	(0.004)	(0.067)	(0.006)	(0.004)	(0.098)	(0.009)	(0.008)
Parents' mental health									
Mother's mental	0.093***	0.005**	0.003*	0.076**	0.004	0.002	0.068	0.005	0.000
health score	(0.025)	(0.002)	(0.002)	(0.034)	(0.003)	(0.002)	(0.047)	(0.004)	(0.003)
Father's mental	0.049*	0.002	-0.003**	0.031	0.003	0.001	0.007	-0.001	0.001
health score	(0.029)	(0.003)	(0.001)	(0.040)	(0.004)	(0.002)	(0.046)	(0.004)	(0.003)
Mother's mental	0.359*	0.020	0.018*	0.071	-0.010	-0.000	-0.265	-0.024	-0.007
health missing	(0.203)	(0.017)	(0.011)	(0.323)	(0.030)	(0.017)	(0.466)	(0.041)	(0.024)
Father's mental	0.057	-0.007	-0.009	-0.419	-0.029	0.001	-0.414	-0.012	0.001
health missing	(0.208)	(0.018)	(0.010)	(0.317)	(0.029)	(0.017)	(0.423)	(0.038)	(0.021)
Constant	6.507***	0.249	0.060	-0.433	-0.198	-0.106	-5.383	-0.389	-0.175
	(2.345)	(0.195)	(0.127)	(6.759)	(0.556)	(0.308)	(8.755)	(0.752)	(0.408)
Observations	6,010	6,010	6,010	6,010	6,010	6,010	4,641	4,641	4,641
R-squared	0.230	0.144	0.071	0.267	0.160	0.074	0.285	0.188	0.088
No. of individuals	3,048	3,048	3,048	3,048	3,048	3,048	2,355	2,355	2,355

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. All estimations include province and year fixed effects.

Table A11: Restricting the sample to only married women

Variables	OLS			Fixed effects			Matching and FE		
	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early marriage	-0.250	-0.007	-0.018						
	(0.349)	(0.029)	(0.013)						
Post treatment	2.833***	0.155***	0.050***	1.975*	0.077	0.028	6.993**	0.206	-0.188
	(0.122)	(0.010)	(0.006)	(1.122)	(0.094)	(0.051)	(3.522)	(0.355)	(0.161)
EarlyMarriage*Post	0.865*	0.065	0.047*	1.118**	0.102**	0.056*	2.395**	0.196**	0.114**
	(0.513)	(0.046)	(0.027)	(0.563)	(0.051)	(0.031)	(1.086)	(0.091)	(0.056)
Demographics									
Religion	-0.333	-0.008	-0.014						
	(0.218)	(0.017)	(0.012)						
Age	0.161**	0.007	0.006	0.289	0.031*	0.010	0.011	-0.027	-0.006
	(0.082)	(0.007)	(0.004)	(0.212)	(0.018)	(0.010)	(0.845)	(0.078)	(0.032)
Age2	-0.004***	-0.000	-0.000*	-0.003*	-0.000	-0.000	-0.003	0.001	0.001
	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.017)	(0.002)	(0.001)
Years married	0.045**	0.003*	0.001	-0.021	-0.011	-0.002	-0.584**	-0.051**	-0.024**
	(0.020)	(0.002)	(0.001)	(0.097)	(0.008)	(0.005)	(0.249)	(0.020)	(0.011)
Married	-0.846***	-0.023	-0.019**	-0.341	-0.023	-0.008	-1.712	0.061	0.060
	(0.202)	(0.016)	(0.009)	(0.403)	(0.034)	(0.022)	(1.880)	(0.169)	(0.073)
Urban	0.021	0.001	-0.001	0.067	0.021	-0.005	-0.219	-0.025	0.025
	(0.116)	(0.009)	(0.006)	(0.230)	(0.020)	(0.012)	(0.665)	(0.062)	(0.030)
Height cm	-0.024***	-0.002***	-0.001	-0.025	-0.003	-0.001	-0.013	-0.003	-0.001
	(0.009)	(0.001)	(0.000)	(0.024)	(0.002)	(0.001)	(0.067)	(0.006)	(0.002)
Work status									
Employed	-1.082	-0.054	-0.139	-0.050	0.103	-0.038	9.000***	0.775***	0.189
	(1.162)	(0.089)	(0.091)	(1.630)	(0.126)	(0.094)	(2.261)	(0.166)	(0.187)
Unemployed	-1.157	-0.061	-0.137	0.441	0.128	0.003	9.364***	0.799***	0.197
	(1.186)	(0.090)	(0.091)	(1.686)	(0.131)	(0.096)	(2.386)	(0.179)	(0.195)
Schooling	-0.169	0.014	-0.120	1.101	0.210	-0.016	10.205***	0.896***	0.228
	(1.176)	(0.090)	(0.091)	(1.672)	(0.131)	(0.096)	(2.211)	(0.160)	(0.186)
House keeping	-1.166	-0.060	-0.138	-0.364	0.087	-0.038	7.036***	0.638***	0.169
	(1.165)	(0.089)	(0.091)	(1.636)	(0.127)	(0.094)	(2.290)	(0.169)	(0.190)
Education									
Education elemen.	0.168	-0.003	0.028	-0.504	-0.071	-0.011	3.566**	0.012	0.183*
	(0.538)	(0.047)	(0.024)	(0.893)	(0.092)	(0.056)	(1.562)	(0.134)	(0.106)
Education junior	-0.118	-0.019	0.017	-0.302	-0.075	-0.049	3.463**	0.140	0.125
	(0.536)	(0.047)	(0.024)	(0.809)	(0.085)	(0.054)	(1.419)	(0.118)	(0.085)
Education senior	-0.198	-0.020	0.013	-0.815	-0.098	-0.066	2.175	0.026	0.061
	(0.533)	(0.047)	(0.023)	(0.901)	(0.090)	(0.062)	(1.346)	(0.119)	(0.080)
Education tertiary	-0.226	-0.027	0.013	-0.839	-0.102	-0.096	0.845	-0.151	0.004
	(0.542)	(0.047)	(0.024)	(0.970)	(0.095)	(0.068)	(1.534)	(0.138)	(0.085)
Poverty proxies									
lnpce	-0.133*	-0.004	0.002	0.081	0.004	0.004	0.285	0.019	-0.017
	(0.069)	(0.006)	(0.003)	(0.105)	(0.009)	(0.006)	(0.338)	(0.032)	(0.017)
Toilet - river/land	0.010	-0.022	-0.006	0.045	0.001	0.006	0.692	-0.003	-0.070
	(0.172)	(0.014)	(0.008)	(0.290)	(0.025)	(0.014)	(0.817)	(0.070)	(0.046)
Cook firewood	0.071	0.008	0.006	-0.175	-0.007	0.007	-0.232	-0.035	0.006
	(0.137)	(0.011)	(0.007)	(0.208)	(0.019)	(0.011)	(0.580)	(0.056)	(0.032)
Household size	0.005	0.003	0.001	-0.049	-0.001	-0.002	-0.001	0.010	-0.001
	(0.032)	(0.003)	(0.002)	(0.053)	(0.005)	(0.003)	(0.165)	(0.014)	(0.009)
Physical health									
Acute morbidity	0.454***	0.028***	0.009***	0.290***	0.020***	0.006***	0.459***	0.023**	0.016***
	(0.027)	(0.002)	(0.002)	(0.038)	(0.003)	(0.002)	(0.109)	(0.012)	(0.006)
Health status	-1.395***	-0.099***	-0.046***	-1.334***	-0.089***	-0.051***	-2.428***	-0.182***	-0.104***
	(0.172)	(0.015)	(0.010)	(0.216)	(0.019)	(0.012)	(0.622)	(0.061)	(0.038)

Days missed	0.085***	0.004***	0.003***	0.041*	0.000	0.002	0.066	0.005	0.003
	(0.019)	(0.002)	(0.001)	(0.022)	(0.002)	(0.001)	(0.098)	(0.007)	(0.006)
Bed ridden	0.126**	0.013***	0.008**	0.186***	0.019***	0.006	0.040	0.018	0.006
	(0.061)	(0.005)	(0.004)	(0.064)	(0.005)	(0.004)	(0.194)	(0.019)	(0.010)
Parents' mental health									
Mother's mental	0.058**	0.001	0.001	0.076*	0.001	0.001	0.114	0.007	-0.002
health score	(0.029)	(0.002)	(0.002)	(0.039)	(0.004)	(0.002)	(0.085)	(0.008)	(0.005)
Father's mental	0.053	0.003	-0.001	0.022	-0.001	0.001	0.074	-0.004	0.004
health score	(0.036)	(0.003)	(0.002)	(0.048)	(0.005)	(0.002)	(0.082)	(0.009)	(0.003)
Mother's mental	0.296	0.013	0.011	0.195	0.009	-0.002	0.973	0.043	0.003
health missing	(0.211)	(0.018)	(0.010)	(0.328)	(0.031)	(0.016)	(0.851)	(0.080)	(0.043)
Father's mental	0.269	0.007	-0.002	-0.414	-0.060*	0.002	0.116	-0.016	-0.005
health missing	(0.230)	(0.019)	(0.011)	(0.341)	(0.031)	(0.018)	(0.714)	(0.070)	(0.033)
Constant	8.388***	0.413**	0.134	1.930	-0.207	0.109	-10.891	-0.628	-0.067
	(2.379)	(0.193)	(0.131)	(6.580)	(0.531)	(0.315)	(17.826)	(1.475)	(0.762)
Observations	6,927	6,927	6,927	6,927	6,927	6,927	2,131	2,131	2,131
R-squared	0.224	0.138	0.067	0.264	0.153	0.065	0.303	0.207	0.140
No of individuals	3,504	3,504	3,504	3,504	3,504	3,504	1,078	1,078	1,078

Robust standard errors in parentheses, clustered at individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All estimations include province and year fixed effects.

Table A12: Marital Status and Age Restrictions

	Marital Status			Age Restriction					
				Full Sample			Alternative Sample		
Variables	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early marriage	0.913*	0.087*	0.061**	1.198**	0.089*	0.053*	1.277**	0.097**	0.060**
	(0.513)	(0.046)	(0.028)	(0.510)	(0.047)	(0.028)	(0.516)	(0.047)	(0.028)
Demographics									
Age	0.304**	0.028**	0.006	0.430***	0.033***	0.012***	0.426***	0.035***	0.012**
	(0.146)	(0.012)	(0.008)	(0.081)	(0.006)	(0.004)	(0.099)	(0.008)	(0.005)
Age2	-0.002	-0.000	0.000	-0.002***	-0.000***	-0.000***	-0.002***	-0.000***	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Years married	-0.076*	-0.012***	-0.006**	-0.075***	-0.007***	-0.002*	-0.102***	-0.010***	-0.005**
	(0.046)	(0.004)	(0.003)	(0.026)	(0.002)	(0.001)	(0.038)	(0.003)	(0.002)
Married	-0.540**	-0.022	-0.012	-0.735***	-0.029	-0.012	-0.718***	-0.032	-0.012
	(0.247)	(0.021)	(0.014)	(0.230)	(0.020)	(0.013)	(0.236)	(0.020)	(0.013)
Urban	-0.029	0.021	-0.017*	0.036	0.031**	-0.013	0.060	0.031**	-0.014
	(0.189)	(0.017)	(0.010)	(0.159)	(0.014)	(0.008)	(0.166)	(0.014)	(0.009)
Height cm	0.000	-0.000	-0.000	-0.010	-0.001	-0.000	-0.008	-0.001	-0.000
	(0.021)	(0.002)	(0.001)	(0.016)	(0.001)	(0.001)	(0.017)	(0.001)	(0.001)
Work status									
Employed	-0.634	-0.044	-0.028	-0.089	-0.011	-0.008	-0.301	0.015	-0.032
	(1.124)	(0.099)	(0.068)	(0.318)	(0.028)	(0.018)	(0.807)	(0.075)	(0.051)
Unemployed	-0.173	0.001	0.010	0.204	0.028	0.017	0.218	0.064	0.001
	(1.169)	(0.102)	(0.070)	(0.404)	(0.034)	(0.022)	(0.862)	(0.079)	(0.053)
Schooling	0.219	0.044	-0.004	0.714*	0.069*	0.004	0.622	0.104	-0.014
	(1.160)	(0.102)	(0.070)	(0.421)	(0.037)	(0.023)	(0.853)	(0.079)	(0.053)
House keeping	-0.872	-0.053	-0.027	-0.247	-0.020	-0.011	-0.458	0.006	-0.034
	(1.124)	(0.099)	(0.068)	(0.315)	(0.028)	(0.017)	(0.809)	(0.075)	(0.051)
Education									
Education elemen.	0.310	-0.011	0.031	-0.456	-0.007	-0.011	-0.037	0.007	0.001
	(0.779)	(0.065)	(0.047)	(0.300)	(0.024)	(0.017)	(0.393)	(0.032)	(0.023)
Education junior	0.255	-0.002	-0.002	-0.444	-0.014	-0.031	-0.067	0.001	-0.015
	(0.780)	(0.065)	(0.048)	(0.389)	(0.031)	(0.022)	(0.469)	(0.038)	(0.027)
Education senior	-0.082	-0.026	-0.013	-0.616	-0.028	-0.044*	-0.281	-0.018	-0.028
	(0.825)	(0.069)	(0.051)	(0.463)	(0.037)	(0.026)	(0.535)	(0.044)	(0.031)
Education tertiary	0.129	-0.017	-0.019	-0.444	-0.023	-0.050*	-0.106	-0.015	-0.037
	(0.864)	(0.073)	(0.054)	(0.521)	(0.044)	(0.030)	(0.591)	(0.050)	(0.035)
Poverty proxies									
lnpce	0.144*	0.010	0.007*	0.097	0.009*	0.005	0.111	0.008	0.006
	(0.082)	(0.007)	(0.004)	(0.061)	(0.005)	(0.003)	(0.068)	(0.006)	(0.004)
Toilet-river/land	0.121	0.005	0.000	0.069	0.005	-0.004	0.032	-0.004	-0.004
	(0.202)	(0.017)	(0.011)	(0.159)	(0.014)	(0.008)	(0.172)	(0.015)	(0.009)
Cook firewood	-0.227	-0.017	-0.005	-0.153	-0.014	-0.001	-0.224*	-0.020*	-0.004
	(0.156)	(0.014)	(0.008)	(0.121)	(0.011)	(0.006)	(0.131)	(0.011)	(0.007)
Household size	-0.034	-0.002	-0.000	0.002	0.000	0.001	0.011	0.001	0.001
	(0.042)	(0.004)	(0.002)	(0.032)	(0.003)	(0.002)	(0.035)	(0.003)	(0.002)
Physical health									
Acute morbidity	0.284***	0.018***	0.006***	0.288***	0.018***	0.007***	0.292***	0.018***	0.007***
	(0.030)	(0.003)	(0.002)	(0.023)	(0.002)	(0.001)	(0.025)	(0.002)	(0.001)
Health status	-1.189***	-0.078***	-0.048***	-0.909***	-0.059***	-0.034***	-1.071***	-0.071***	-0.041***
	(0.168)	(0.015)	(0.010)	(0.120)	(0.010)	(0.007)	(0.134)	(0.012)	(0.008)
Days missed	0.043**	0.002	0.001	0.058***	0.003***	0.002***	0.062***	0.003***	0.003***
	(0.018)	(0.002)	(0.001)	(0.011)	(0.001)	(0.001)	(0.014)	(0.001)	(0.001)
Bed ridden	0.171***	0.015***	0.006*	0.123***	0.011***	0.006**	0.124***	0.012***	0.005**
	(0.050)	(0.004)	(0.003)	(0.037)	(0.003)	(0.003)	(0.041)	(0.004)	(0.002)

Parents' mental health									
Mother's mental	0.071**	0.004	0.001	0.066**	0.004	0.002	0.065**	0.003	0.002
health score	(0.030)	(0.003)	(0.002)	(0.029)	(0.003)	(0.002)	(0.029)	(0.003)	(0.002)
Father's mental	0.039	0.002	0.001	0.032	0.002	0.001	0.032	0.002	0.001
health score	(0.037)	(0.003)	(0.002)	(0.037)	(0.003)	(0.002)	(0.037)	(0.003)	(0.002)
Mother's mental	0.162	0.005	0.003	0.214	0.014	0.007	0.250	0.017	0.008
health-missing	(0.271)	(0.025)	(0.014)	(0.238)	(0.022)	(0.013)	(0.244)	(0.022)	(0.013)
Father's mental	-0.358	-0.041	-0.007	-0.285	-0.037	-0.005	-0.308	-0.039*	-0.006
health-missing	(0.275)	(0.025)	(0.015)	(0.265)	(0.024)	(0.014)	(0.268)	(0.024)	(0.015)
Separated/divor-	0.720	0.080	0.089*						
ced/widowed	(0.884)	(0.075)	(0.054)						
Constant	-1.497	-0.544	-0.075	-7.182**	-0.741***	-0.269	-6.884*	-0.745**	-0.278
	(5.619)	(0.464)	(0.284)	(3.570)	(0.275)	(0.170)	(4.032)	(0.340)	(0.218)
Observations	11,386	11,386	11,386	18,861	18,861	18,861	16,219	16,219	16,219
R-squared	0.278	0.162	0.068	0.265	0.151	0.065	0.271	0.156	0.068
No of individuals	5,765	5,765	5,765	9,550	9,550	9,550	8,207	8,207	8,207

Robust standard errors in parentheses, clustered at individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All estimations include province and year fixed effects.

Table A13: Alternative matching

Variables	CES-D Score (1)	Dep. (2)	Severe Dep. (3)
Post treatment	1.870	0.142	0.020
	(4.007)	(0.345)	(0.146)
EarlyMarriage*Post	4.316***	0.283**	0.161**
	(1.299)	(0.116)	(0.080)
Demographics			
Age	-0.180	-0.043	-0.001
	(1.020)	(0.084)	(0.043)
Age2	0.012	0.002	0.000
	(0.019)	(0.002)	(0.001)
Years married	-0.788***	-0.055**	-0.019
	(0.296)	(0.026)	(0.015)
Married	0.583	0.007	0.022
	(0.984)	(0.090)	(0.053)
Urban	0.019	-0.005	0.060
	(0.728)	(0.069)	(0.042)
Height_cm	-0.037	0.000	-0.003
	(0.085)	(0.006)	(0.004)
Work status			
Employed	9.356***	0.955***	-0.131
	(1.996)	(0.179)	(0.115)
Unemployed	8.857***	0.842***	-0.102
	(2.274)	(0.204)	(0.117)
Schooling	9.813***	0.950***	-0.106
	(2.196)	(0.198)	(0.115)
House keeping	6.805***	0.766***	-0.182
	(2.222)	(0.206)	(0.133)
Education			
Education elemen.	-1.118	-0.284*	-0.076
	(2.733)	(0.168)	(0.093)
Education junior	0.378	-0.097	-0.128
	(2.525)	(0.134)	(0.084)
Education senior	-0.154	-0.127	-0.183**
	(2.613)	(0.138)	(0.092)
Education tertiary	-0.846	-0.251	-0.153
	(2.711)	(0.157)	(0.097)
Poverty proxies			
lnpce	0.373	0.007	-0.006
	(0.453)	(0.039)	(0.025)
Toilet-river/land	0.046	-0.082	0.052*
	(1.028)	(0.081)	(0.030)
Cook firewood	-0.180	0.029	0.062
	(0.840)	(0.071)	(0.057)
Household size	0.206	0.009	0.005
	(0.208)	(0.017)	(0.014)
Physical health			
Acute morbidity	0.453**	0.024	0.020**
	(0.186)	(0.016)	(0.010)
Health status	-2.616***	-0.206***	-0.056
	(0.794)	(0.066)	(0.046)
Days missed	0.099	0.007	0.003
	(0.101)	(0.008)	(0.005)
Bed ridden	0.432*	0.044*	0.023
	(0.232)	(0.024)	(0.019)

Parents' mental health			
Mother's mental	-0.069	-0.009	-0.012**
health score	(0.098)	(0.009)	(0.005)
Father's mental	0.080	0.002	0.001
health score	(0.099)	(0.009)	(0.004)
Mother's mental	-0.479	-0.070	-0.110
health-missing	(1.217)	(0.103)	(0.067)
Father's mental	-0.004	0.002	0.029
health-missing	(0.940)	(0.085)	(0.051)
Constant	-5.405	-0.543	0.644
	(18.899)	(1.414)	(0.833)
Observations	1,186	1,186	1,186
R-squared	0.340	0.245	0.152
No of individuals	602	602	602

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1. All estimations include year and province fixed effects.

Table A14: Coarsened Exact Matching Summary

	Control (Early marriage = 0)	Treatment (Early marriage = 1)
All	3892	160
Matched	469	133
Unmatched	3423	27

Table A15: Covariate Balance

Pre-match multivariate L1 distance: 0.8952

	Pre-match univariate imbalance		Sample mean	
	L1	Mean difference	Control (EM = 0)	Treatment (EM = 1)
Religion	0.067	0.067	0.898	0.963
Age	0.785	-8.710	25.123	16.431
Urban	0.172	-0.172	0.603	0.431
Schooling	0.287	0.287	0.170	0.456
Education senior	0.022	-0.022	0.460	0.438
Toilet - river/land/sea	0.100	0.100	0.112	0.212
Acute morbidity	0.115	0.181	2.357	2.538

Post-match multivariate L1 distance: 0.3630

	Post-match univariate imbalance		Sample mean	
	L1	Mean difference	Control (EM = 0)	Treatment (EM = 1)
Religion	0.000	0.000	0.977	0.977
Age	0.105	-0.056	16.500	16.444
Urban	0.000	0.000	0.444	0.444
Schooling	0.000	0.000	0.526	0.526
Education senior	0.000	0.000	0.474	0.474
Toilet - river/land/sea	0.000	0.000	0.113	0.113
Acute morbidity	0.000	0.000	2.391	2.391

Table A16: CRE and HT Estimations

Variables	CRE			HT		
	CES-D Score	Dep.	Severe Dep.	CES-D Score	Dep.	Severe Dep.
	(1)	(2)	(3)	(4)	(5)	(6)
Age married	-0.028*	-0.002	-0.002**	-0.267	-0.026*	-0.004
	(0.015)	(0.001)	(0.001)	(0.170)	(0.014)	(0.009)
Demographics						
Religion	-0.474**	-0.018	-0.024**	-1.728**	-0.095*	-0.042
	(0.204)	(0.017)	(0.012)	(0.676)	(0.053)	(0.026)
Age	0.264*	0.012	-0.000	0.222	0.005	-0.002
	(0.159)	(0.013)	(0.008)	(0.137)	(0.011)	(0.007)
Age2	-0.001	0.000	0.000	-0.001	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Urban	0.155	0.027	-0.010	0.225	0.034*	0.001
	(0.220)	(0.020)	(0.012)	(0.238)	(0.021)	(0.012)
Height cm	0.017	0.001	-0.000	0.022	0.001	0.000
	(0.024)	(0.002)	(0.001)	(0.026)	(0.002)	(0.001)
Work status						
Employed	-1.378	-0.143	-0.074	-2.395**	-0.221**	-0.120
	(1.223)	(0.109)	(0.085)	(1.209)	(0.108)	(0.082)
Unemployed	-1.310	-0.137	-0.014	-2.208	-0.185	-0.073
	(1.398)	(0.119)	(0.094)	(1.567)	(0.130)	(0.099)
Schooling	-0.454	-0.112	-0.079	-0.310	-0.080	-0.077
	(1.350)	(0.113)	(0.087)	(1.454)	(0.112)	(0.083)
House keeping	-1.602	-0.152	-0.074	-2.592**	-0.230**	-0.119
	(1.223)	(0.108)	(0.085)	(1.208)	(0.108)	(0.082)
Education						
Education elemen.	0.152	-0.005	0.029	0.535	0.045	0.036
	(0.923)	(0.074)	(0.056)	(0.990)	(0.076)	(0.063)
Education junior	-0.135	-0.005	-0.017	0.262	0.043	-0.010
	(0.944)	(0.075)	(0.059)	(1.018)	(0.079)	(0.066)
Education senior	-0.964	-0.063	-0.045	-0.402	0.002	-0.017
	(1.008)	(0.081)	(0.063)	(1.090)	(0.085)	(0.072)
Education tertiary	-0.364	-0.015	-0.042	0.538	0.100	-0.002
	(1.086)	(0.090)	(0.071)	(1.174)	(0.095)	(0.082)
Poverty proxies						
lnpce	-0.053	-0.004	0.003	-0.047	0.002	0.005
	(0.092)	(0.008)	(0.005)	(0.100)	(0.009)	(0.005)
Toilet-river/land	0.054	-0.003	-0.000	0.038	0.000	0.002
	(0.223)	(0.019)	(0.012)	(0.232)	(0.020)	(0.012)
Cook firewood	-0.161	-0.012	-0.004	-0.208	-0.015	-0.012
	(0.178)	(0.016)	(0.009)	(0.187)	(0.017)	(0.010)
Household size	-0.041	-0.003	-0.001	-0.063	-0.006	-0.001
	(0.047)	(0.004)	(0.003)	(0.053)	(0.005)	(0.003)
Physical health						
Acute morbidity	0.256***	0.018***	0.006***	0.239***	0.016***	0.005**
	(0.034)	(0.003)	(0.002)	(0.037)	(0.003)	(0.002)
Health status	-1.085***	-0.078***	-0.044***	-1.037***	-0.071***	-0.037***
	(0.188)	(0.017)	(0.011)	(0.198)	(0.018)	(0.011)
Days missed	0.040**	0.000	0.001	0.031	-0.001	0.001
	(0.019)	(0.002)	(0.001)	(0.019)	(0.002)	(0.001)
Bed ridden	0.200***	0.016***	0.006*	0.162***	0.014***	0.006
	(0.058)	(0.005)	(0.004)	(0.057)	(0.005)	(0.004)
Parents' mental health						
Mother's mental	0.047	-0.001	0.001	0.065	0.003	0.001
health score	(0.041)	(0.003)	(0.002)	(0.055)	(0.004)	(0.002)

Father's mental	0.111**	0.008	0.003	0.122*	0.013**	0.002
health score	(0.057)	(0.005)	(0.003)	(0.073)	(0.006)	(0.003)
Mother's mental	0.139	-0.000	0.017	0.379	0.029	0.002
health-missing	(0.219)	(0.019)	(0.011)	(0.429)	(0.038)	(0.020)
Father's mental	0.227	-0.002	-0.014	-0.607	-0.079*	-0.029
health-missing	(0.268)	(0.024)	(0.014)	(0.479)	(0.041)	(0.023)
Constant	18.146***	1.337***	0.424**	7.811	0.639	0.258
	(2.824)	(0.234)	(0.170)	(5.782)	(0.501)	(0.283)
Observations	9,021	9,021	9,021	9,021	9,021	9,021
No of individuals	5,118	5,118	5,118	5,118	5,118	5,118

Robust standard errors in parentheses, clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1
All estimations include year and province fixed effects. For brevity, the time averages of the CRE model are not reported. In estimating the HT model, age married is assumed as a time-invariant endogenous variable and religion dummy as a time-invariant exogenous variable. Dummy variable for urban and provincial dummy variables are considered as time-variant exogenous whereas the remaining covariates were assumed to be time-variant endogenous.

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Chapter 3

The Long Shadow of Child Labour on Adolescent Mental Health

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Abstract

This study examines the causal effect of child labour on the long-term mental health of children using longitudinal household data from the Indonesia Family Life Survey (IFLS). We use legislative minimum wage and the number of family-owned businesses as instruments to address the endogeneity bias of child work. Results from the instrumental variable estimation indicate that child labour negatively affects mental health. We find heterogeneity in the effect of child labour. Specifically, working for wages increases the mental health score (CES-D score) by approximately 5.9 points. This pushes the average score above the cut-off, suggesting the presence of significant depressive symptoms. On the contrary, there is no significant impact of working as a child in family enterprises on adolescent mental health. We further find that religiosity and social capital are potential mediating factors that could subdue the adverse long-term effects of child labour on mental health.

Keywords: Child labour; mental health; instrumental variable; poisson regression model; Indonesia

JEL classification: I14, I15, I31, J82

3.1 Introduction

Child labour is a global concern, where 1 in 10 children are engaged in child labour accounting for a total of 152 million children worldwide. Notably, half of these children (73 million) are involved in hazardous work that directly endangers their health and safety (ILO, 2017). Despite the nature and extent of child labour, any form of child work is detrimental to children's physical and mental health development.[1] Factors such as lack of experience, exposure to dangerous chemicals or exhaustion due to long hours can cause physical injuries and morbidities (Graitcher & Lerer, 1998), with some injuries leading to persistent health problems even into adulthood (Edmonds, 2007).

There is empirical evidence that child labour affects a child's short and long term physical health (see Beegle et al., 2009; Guarcello et al., 2004; Kana et al., 2010; O'Donnell et al., 2005; Wolff & Maliki, 2008). Moreover, working as a child could also result in psychological effects as child labour can be identified as a type of childhood adversity. Studies from psychology show that being exposed to adverse events in childhood have implications on both short- and long-term mental wellbeing (Hammen, 2005; Heim & Nemeroff, 2001; Kendler et al., 1999). Frequent and prolonged exposure to adversity can inevitably lead to toxic stress. This, in turn, could damage the structure of the developing brain leading to mental health disorders such as depression that may arise immediately or years later (Franke, 2014; National Scientific Council on the Developing Child, 2012).

In recent years, there is a growing concern on mental wellbeing, as poor mental health among young people is on the rise. According to the World Health Organisation (2018), 10 to 20 per cent of children and adolescents[2] experience mental disorders leading to poor mental health.[3] Notably, it is shown that half of all mental illnesses begin by the age of 14 (Kessler at al., 2007), which reflects the importance of ensuring a safe and secure childhood for all children.

[1] The terms 'child labour' and 'child work' are used interchangeably.

[2] The World Health Organisation (WHO) defines an adolescent as any person between ages 10 and 19 years.

[3] As cited in World Health Organisation (26 February 2019). Retrieved from https://www.who.int/mental_health/ maternal-child/child_adolescent/en/

In this study, we examine the impact of child labour on adolescent mental health. By using a rich data source, Indonesia Family Life Survey (IFLS) and using an instrumental variable approach as the identification strategy, we attempt to answer three research questions: (1) Does working as a child affect adolescent mental health? (2) If so, does the effect vary with the type of work that they perform, that is whether they work for wages or in a family business? (3) What factors could mediate the long-term effects of child labour on mental health?

In addressing these questions, we make several contributions to the literature on child labour. First, it adds to the evidence of health effects of child labour, specifically in relation to mental health. Compared to the number of studies on the physical health effects of child labour, empirical studies on mental health effects are limited. Therefore, to the best of our knowledge, we provide first evidence on the causal effect of child labour on adolescent mental health.[4] The mental health is assessed using one of the commonly used measures of 10-item Centre for Epidemiological Studies Depression Scale (CES-D-10) (Andresen et al., 1994). In general, longitudinal datasets which consist of data on such validated measure of mental health are scarce, particularly with regard to less developed countries. Given that child labour is mostly an issue in the less developed countries, our study would provide important insights on adolescent mental health effects of child labour.

Second, our rich data source also allows us to identify the heterogeneous effect of child labour based on whether the child has worked for wages or in a family business. Since health effects of child work can greatly depend on the type of work activities performed by the children, such classification would enable us to understand the magnitude of each type of work on mental health.

Third, we attempt to examine potential factors that could mediate the effect of child labour on adolescent mental health. In this regard, we consider two factors - religiosity and social capital, based on psychology literature and the availability of data. Given the high prevalence of child labour especially in developing countries, understanding the possible mechanisms that could minimise the negative repercussions of child labour is

[4]We acknowledge that there is a recent study by Trinh (2020) which examines the causal effect of child labour on contemporaneous mental health. Our study differs from this as we focus on the long-term mental health effects.

crucial for policy intervention.

Child labour occurs as a result of multiple factors such as social, economic and political forces. Among them, economics vulnerabilities connected with poverty and shocks are considered to be the root cause of child labour (Edmonds, 2007). In view of Jafarey and Lahiri (2005), the nexus between poverty and child labour occurs through various channels. In particular, for poor households with no access to credit, the income earned by the child is essential as an alternative source of income. Further, as a result of high marginal utility of such limited income, households are compelled to substitute child's education for work, thus inducing children to supply more labour (Jafarey & Lahiri, 2005). This suggests that the decision to work as a child is plausibly endogenous and therefore identifying the causal effect of child labour on adolescent mental health is challenging.

We address the potential endogeneity problem using an instrumental variable (IV) framework, by considering two instruments: the minimum wage proposed by Sim et al. (2017), and the number of family-owned businesses by the household. The results reveal that child labour has a substantial negative impact on a child's long-term mental health status. Moreover, we find heterogeneity in the effect of child labour where working as a child for wages increases the mental health score (CES-D score) by approximately 5.9 points. This pushes the average score well above the cut-off of 10, suggesting the presence of significant depressive symptoms. On the contrary, there is no significant impact of working as a child in family enterprises on adolescent mental health. Additionally, we find that religiosity and social capital play a role in mediating the adverse long-term effects of child labour on mental health. The findings are robust to changes in child labour definition and model specifications.

The rest of the chapter is organised as follows. Section 3.2 provides a brief background on child labour and mental health. Section 3.3 reviews the existing empirical literature. Section 3.4 describes the data source and the variables used in the study. Section 3.5 outlines the methodology. Section 3.6 and 3.7 presents the empirical results and their robustness checks. Section 3.8 discusses the findings. The concluding remarks are given in Section 3.9.

3.2 Background

3.2.1 Global Estimates of Child Labour and Mental Health

Child labour is defined as all children between the age of 5 to 15 years who are economically active (ILO, 2002). The recent statistics show that almost ten per cent of children are in child labour worldwide accounting for a total of 152 million (ILO, 2017). The prevalence of child labour differs based on both the gender and age of children. Boys are more likely to engage in child labour where the proportion is 58 per cent compared to that of 42 per cent of girls. In terms of age, surprisingly, younger children have a higher risk of child labour. Specifically, 48 per cent of child workers are among the age group of 5 to 11, and only 28 per cent of them are aged 12 to 14 years.

Child labour is, in fact, harmful not only for the child's contemporaneous health but also for future adult health. Specifically, as a childhood adversity, the psychological stress or trauma that the child workers experience may lead to persistent mental health disorders. If we consider the global estimates, in general, 10 to 20 per cent of children and adolescents experience mental disorders leading to poor mental health (WHO, 2018). The consequences of poor mental health are mainly visible during the adolescence period. For instance, depression is identified as the ninth major cause of disability among adolescents worldwide. Self-harm is the third main source of death for adolescents aged 15 to 19 years (WHO, 2018)[5]. According to Kessler et al. (2007), the first onset of mental disorder usually occurs in childhood, where half of all lifetime mental illnesses begin by the age of 14. This shows the importance of ensuring a safe and secure childhood for all children. One aspect of this would be to eliminate child labour, specifically that of hazardous nature.

3.2.2 Child Labour and Mental Health in Indonesia

As a developing country, Indonesia has a high incidence of child labour. Across Indonesia, 6.9 per cent of children were in child labour in 2009 (BAPPENAS & UNICEF, 2017).

[5] As cited in World Health Organisation (26 February 2019). Retrieved from https://www.who.int/mental_health/ maternal-child/adolescent/en/

Alarmingly, close to half of these child workers are engaged in hazardous work (BAPPENAS & UNICEF, 2017). In line with global trends, boys are more likely to work where the percentage is 7.7 per cent compared to six per cent of girls. Moreover, child labour is mostly prominent in rural areas where children from rural areas are twice as more likely to be in child labour compared to children from urban areas (US Department of Labour's Bureau of International Labour Affairs, 2015).

There exists a considerable stigma around mental health issues in Indonesia, where individuals with mental health problems are often stereotyped and discriminated. Hence, individuals are reluctant to seek medical treatment or professional counselling. This has led to the lack of official data on mental health for adults as well as children.[6] According to the World Health Organisation (2017), 6.4 per cent of individuals aged 15 years and above experience mental disorders in Indonesia. Furthermore, during the period of 1990 to 2006, the disability-adjusted life year (DALY)[7] for depressive disorder in Indonesia has increased by 37.5 per cent (Mboi et al., 2018). The corresponding increase for the period from 2006 to 2016 is 19.8 per cent. Based on their systematic analysis, mental disorder has become one of the major causes of disability in 2016 when compared to 1990 (Mboi et al., 2018).

3.3 Related Literature

This study relates to the literature on the impacts of child labour on health. Though there is a plethora of studies on examining the effect of child labour on various educational outcomes, evidence on long-term health effects of child work is limited (Beegle et al., 2009; Guarcello et al., 2004; Kana et al., 2010; O'Donnell et al., 2005; Wolff & Maliki, 2008). The relationship between child work and health is complicated, as it can be either direct or indirect, positive or negative, causal or spurious (O'Donnell et al., 2002).[8]

[6] According to the World Health Organisation, data on mental disorders are unavailable for two-thirds of countries.

[7] The disability-adjusted life year (DALY) quantifies the overall disease burden. This measures the number of years lost due to disability, ill-health or early death (Mboi et al., 2018).

[8] See O'Donnell et al. (2002) for an extensive discussion on the relationship between child labour and health.

O'Donnell et al. (2005) present empirical evidence on the effect of working as a child on physical health, using longitudinal data from Vietnam. This study uses panel data, which facilitate in identifying both contemporaneous and long term effects (after five years) of child labour on health. They use self-assessment of physical health status and anthropometric measures of height growth and weight-for-age Z-score as the outcome variables. To address the problem of endogeneity, they employ a set of instruments such as rice price, land holdings, migration ratio and school quality indicators. The findings reveal that child labour does not have a negative effect on physical health in the short-run but in the long run particularly for girls. A similar study was conducted by Beegle et al. (2009) on the effect of child labour on physical health using the same longitudinal data set from Vietnam.[9] However, this study uses a different set of instrumental variables – the price of rice and disaster shocks - to examine the impact on body mass index and two self-reported physical health measures. In contrast to O'Donnell et al. (2005), this study does not find any significant effect of child labour on both short and long-term health. Despite using the same data set, the contradictory findings of the above two studies may be due to several reasons. First, the two studies differ in terms of sample selection. Specifically, the study of O'Donnell et al. (2005) focuses on children aged between 6 and 17 years old whereas that of Beegle et al. (2009) considers younger children, aged 8 to 13 years old. Second, there are differences in the definition of child labour used in the two studies. Third, there are also considerable differences in the econometric specifications of the two studies. For instance, O'Donnell et al. (2005) consider the zero values of working hours of non-working children, whereas Beegle et al. (2009) do not. This implies that when identifying the causal impact of child labour on health, it is important to consider not only the econometric methodology but also the choice of relevant outcome variables as well as appropriate definitions since such factors could manipulate the findings (Wolff and Maliki, 2008).

In a more recent study, Sim et al. (2017) examine the effect of child labour on the human capital which is proxied by three outcome variables – educational attainment, mathematics and cognitive skills and pulmonary function. This study uses panel data

[9] In addition to health, this study also looks at the impact on education and labour market outcomes.

from the third and fourth waves of the Indonesia Family Life Survey (i.e. IFLS 3 in 2000 and IFLS 4 in 2007). Contrary to previous studies, the provincial legislated minimum wage is employed as an instrument to address endogeneity. The findings reveal strong negative effects of child work on the growth of lung capacity as well as mathematics skills in the next seven years. However, there is no significant effect on the development of cognitive skills and educational attainment.

Considering the number of hours worked by children in rural Cambodia, Kana et al. (2010) assert that child labour does not impair the child's health status. The study further finds that working as a child can have a positive effect on physical health provided that the child works within the threshold level, which is estimated to be less than 45 hours per week. This study uses self-assessed health status, BMI for age z-score and height for age z-score as proxies for children's health. The positive health effects of child labour are justified by the fact that most of the children in rural Cambodia engage in light work such as fishing and cattle rearing which are not necessarily harmful for children's physical and mental health. However, in a similar study, Guarcello et al. (2004) show that the intensity of child work does exert a significant adverse effect on the health outcomes of children as proxied by self-reported illness and injuries. Drawing evidence from three countries - Cambodia, Bangladesh and Brazil, the findings reveal that each hour of work performed during a week increases the probability of falling ill by approximately 0.2 points. Furthermore, it is also shown that children in agriculture are more likely to suffer injuries than those in the manufacturing and service sectors.

In addition to the above studies on physical health effects of child labour, a recent study by Trinh (2020) examines the contemporaneous effect of child labour on mental health. Using data from two developing countries - India and Vietnam, and employing rainfall as an instrument, the results indicate that working as a child has a strong negative effect on current mental health. Moreover, this study also shows heterogeneity in the effect. Specifically, the impact of child labour on mental health is greater for boys compared to girls. Similar to Kana et al. (2010), the study finds that household work which can be classified as light work tend to have a positive effect on mental health.

Our study is also related to the extensive body of research on the relationship between early-life circumstances and adult outcomes. Many of these studies examine the effects on physical health, education and labour market outcomes (see Alderman et al., 2001; Banerjee et al., 2010; Behrman et al., 2014; Cornwell & Inder, 2015; Maccini & Young, 2009 among many others). However, recently there has been a growing number of studies on the effect of early-life experiences on adult mental health. In this regard, few studies have investigated the effects of early-life exposure to weather shocks on mental health in later life. These provide evidence that various weather shocks such as droughts, typhoons and rainfall shocks experienced during childhood lead to mental health disorders and disabilities as an adult (Dinkelman, 2017; Liu et al., 2016; and Pasha et al., 2018). Similarly, Adhvaryu et al. (2018) estimate the mental health effects of early-life income shocks. Considering the changes in cocoa prices, the authors find that a positive income shock can significantly decrease the probability of severe mental distress in later life in Ghana.

In contrast to the above studies, a limited number of studies evaluate the effect of childhood adversity on adult mental health. Evidence from psychological research suggests that exposure to stressful and adverse events in childhood is a major cause of developing depression (Hammen, 2005; Heim & Nemeroff, 2001; Kendler et al., 1999; McMahon et al., 2003). Frequent and prolonged exposure to adversity can result in toxic stress. This may damage the structure of the developing brain leading to significant mental health disorders such as depression that may occur immediately or years later (Franke, 2014; National Scientific Council on the Developing Child, 2012). Moreover, the adverse effects of intense stressors are in fact long-lasting (Shaw, 2003) where it is shown that children with high levels of exposure to adversity are more than four times as likely to develop a mental disorder during adulthood compared to those children who have not (McLaughlin et al., 2012).

Considering evidence from causal studies on childhood adversity and mental health, Singhal (2018) shows that those who were exposed to the American war in Vietnam during their childhood experience significantly worse mental health as adults. A similar finding is also reported by Kesternich et al. (2014), where exposure to the events of World War II increased the probability of suffering from depression as adults. Additionally, it is found that experience of dispossession and hunger periods (Kesternich et al., 2014), stress and malnutrition (Singhal, 2018) are some of the channels through which events such as war can have a lasting impact on the individual's health status. Gong et al. (2017) investigate the effect of a mandatory rustication program ('send down' policy)[10] implemented during China's cultural revolution on the mental health outcomes of individuals. The findings suggest that rusticated youth were more likely to develop mental disorders later in life.

To the best of our knowledge, our study is the first to examine the impact of child work, which can also be considered as a childhood adversity, on adolescent mental health. Though there are a few studies that have identified the effect of child labour on various aspects of physical health such as anthropometric measures and health status (Beegle et al., 2009; O'Donnell at al., 2005; Sim et al., 2017) and one study on contemporanous effect of child labour on mental health (Trinh, 2020), there is no empirical evidence on long-term mental health effects of child work. Therefore, this study seeks to address this evidence gap.

3.4 Data

3.4.1 Data Source and Sample of Interest

We use data from the Indonesia Family Life Survey (IFLS). The IFLS is an ongoing longitudinal survey with unique features such as low attrition (see Section 1.3.2). Currently, there are 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 only use data from the recent two waves of the IFLS (2007 and 2014) since questions on mental health and childhood adverse events were first included in 2007 and 2014 waves.

Our sample for analysis is restricted to individuals who are observed in both time periods, labelled as 2007 and 2014. Based on the definition of child labour, we consider only those children between the age of 5 to 14 years old in 2007 who are deemed to be economically

[10] This was a national movement in which 17 million junior and senior school students residing in cities were mandated to leave their urban homes to live and work in rural areas.

active. According to Edmonds (2007), participation in both wage work and unpaid work as part of a family business are referred to as 'economically active'. This means household work or chores performed by children are not considered as child labour. The data on child labour is extracted from the child module of IFLS 4 (2007 wave), which is administered to children below 15 years old.[11] As our main variable of interest, we construct a binary variable which takes on 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.[12]

It is important to mention that we examine the effect of child labour on mental health after a period of seven years, that is, the effect of working as a child in year 2007 on the mental health status in 2014. This is due to two reasons: (1) mental health data are reported to those individuals who are 15 years and above, (2) by definition, child labour should include children between the age of 5 to 14 years. Accordingly, our sample consists of 4,358 individuals from 3,788 households. After excluding observations with missing responses, 3,839 observations are used in the estimation. Approximately eight per cent in our sample have worked as children either for wages or in a family business in 2007, which corresponds to the actual percentage of child labour in Indonesia.

3.4.2 Outcome Variable

Mental health status is measured using the 10-item Centre for Epidemiological Studies Depression Scale (CES-D-10) (Radloff, 1977), which is a self-reported measure of depression based on ten questions. As a validated scale, it has consistent performance in both developed and developing countries (Mackinnon et al., 1998) and thus is widely used in research.

The ten questions refer to how often the respondent experienced each of the depressive symptoms during the past week. All questions include four response categories from 0 to 3 (0 = rarely or none of the time; 1 = some or little of the time; 2 = moderately

[11]This means the respondent is usually a child below 15 years old. Sometimes the questions are answered by an older sibling or another household member such as mother, aunt or grandmother who deemed the most knowledgeable source of information for the child.

[12]The IFLS also provides 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.

or much of the time; 3 = most or almost all the time) (Radloff, 1977). The CES-D score is calculated by obtaining the sum of these ten responses, with positively phrased statements reverse-coded.[13] This ranges from 0 (no depression) to 30 (severe depression), meaning a higher score reflects a higher level of depressive symptoms. The Cronbach's α is 0.728, which suggests an acceptable level of internal consistency. As our main outcome variable, we use the composite score obtained from the adult module of IFLS 5 (2014 wave). Importantly, the questions on mental health are only reported for individuals who are 15 years and above (module B3B-KP). Therefore, we do not have the score for the individual as a child in 2007.

3.4.3 Other Covariates

We control for a set of extensive characteristics that are well established in the mental health literature. These are classified as socio-demographic factors, adverse events, religiosity and social capital, health status and habits and behavioural factors. Social-demographic factors include gender, age, marital status, employment status and education level of the corresponding individual. The monthly per capita expenditure is used as a proxy for economic status. This includes both food and non-food expenditure. As poverty is considered to be an important determinant of mental health (Currie, 2009; Dzator, 2013; Myer et al., 2008; Tampubolon & Hanandita, 2014) we also consider dwelling conditions such as whether the household uses nearby river, land or sea as the toilet and whether the household uses firewood for cooking as proxies for poverty. Mental health can also depend on the past income status, hence we include the monthly per capita income and dwelling conditions pertaining to previous wave (2007) in our estimation.

Experience of adverse events increases the risk of depression (Neria et al., 2008; Rehdanz et al., 2015; Satcher et al., 2007). This includes both contemporaneous as well as past events. Literature in psychology has shown that stressful or adverse events experienced as a child can have a negative impact on mental health as an adult (see Fryers & Brugha, 2013; Maclean at al., 2016). The recent wave 5 of IFLS includes a battery of questions

[13] Please see Table B1 in Appendix for the sample questionnaire.

that allows us to identify whether the respondents were exposed to adversity during their childhood.[14] Based on these questions, we include several indicator variables which identify the health status in childhood, whether the individual was bedridden and/or experienced hunger as a child. Furthermore, we control for adverse parental characteristics experienced in childhood, such as whether the parents used to smoke or drink heavily, had poor mental health problems and were no longer married. In addition to past events, we also include covariates for current stressful life events such as accidents, crime[15], natural disasters and economic disruptions.

The impact of religion on mental health has been highlighted in several studies (see Koenig et al. 2012). Most of these studies show that being religious reduces psychological distress and leads to better mental health. Hence, we include a dummy variable which takes on a value of 1 if the individual is reported to be very religious or somewhat religious and 0 otherwise. Social capital, which usually refers to the network of relationships among people in a society, is shown to be inversely associated with mental disorders (Johnson et al., 2017; Tampubolon, 2012). Therefore, we use two variables - willingness to help and participation in community activities as proxies for social capital.

Mental health also depends on physical health status (Liew, 2012). To account for physical health, we include controls, such as the number of chronic conditions ever diagnosed with, number of acute morbidities experienced during the last four weeks, self-reported health status and the number of days missed during the last four weeks in primary activity due to poor health. Moreover, under behavioural factors, smoking habits (Liew & Gardner, 2016), dietary habits such as adequate consumption of fruits and vegetables (Li et al., 2017; Mujcic & Oswald, 2016; Ocean et al., 2019), consumption of soft drinks (Lien et al., 2006) and the involvement in physical activities (Rebar et al., 2015) are found to be correlated with depression and, thus, considered as covariates. 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). The BMI is calculated as weight in kilograms (kg) divided

[14]These questions are included in the two new modules (B3B_EH and B3B_SA) of the IFLS 2014 (wave 5). For example; (1) During your childhood (from birth to 15 years), because of a health condition, were you ever confined to bed or home for one month or more? (Response options - Yes or No); (2) Did you experience hunger in your childhood? (Response options - Yes or No); (3) When you were 12, did any of your parents smoke? (Response options - Yes or No) and so on.

[15]Data on crime are extracted from IFLS 2007 (wave 4) as they are removed from IFLS 2014 (wave 5).

by height in metres squared (m^2) where the criterion for Asian adults proposed by the World Health Organisation (2000) is used as the classification basis.[16]

Additionally, we consider the regional heterogeneity by including dummy variables for urban/rural residence as well as individual provinces. Table A2 provides a complete list of variables used in the study. Note that apart from child labour status, proxies for past income and crime which are observed in 2007, all other covariates are observed in 2014, including the main outcome variable of mental health.

3.4.4 Descriptive Statistics

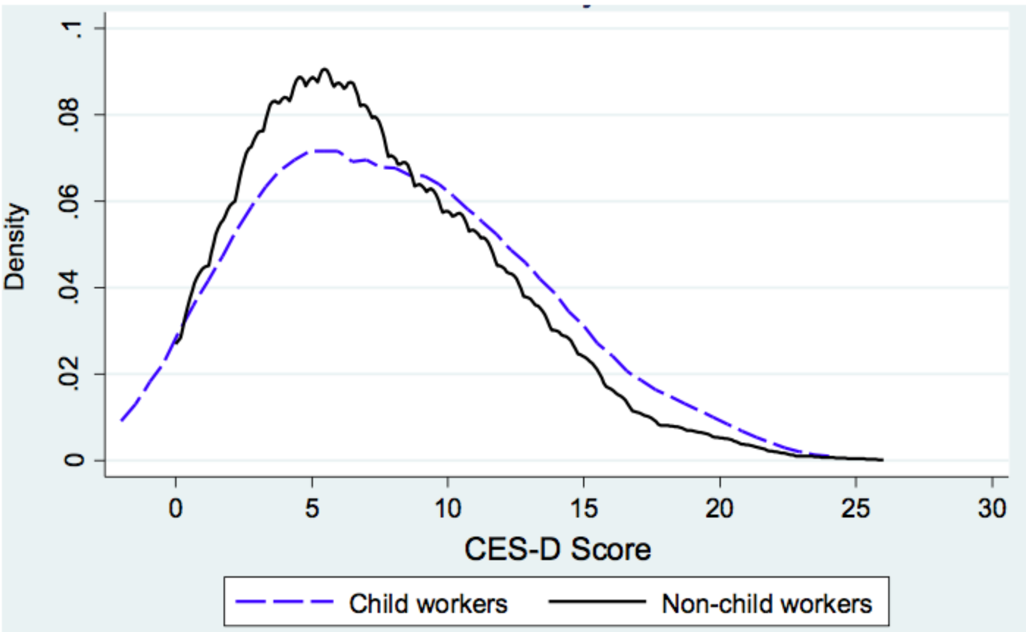
Descriptive statistics are shown in Table B3 in Appendix. The average mental health score of our sample is 7.46. A CES-D score of 10 or above (based on the 10-item scale) indicates the presence of clinical depression (Andresen et al., 1994). The sample means of mental health score for child workers and non-child workers are also shown in Table B3. Figure 3.1 illustrates the distribution of the CES-D score by child work status. Overall, non-child workers have significantly lower mental health score (i.e. lower depressive symptoms) as adolescents than those who worked as children.

Table B3 also reports descriptive statistics of other covariates. Approximately, half of our sample is comprised of girls and the average age is 17.6 years. Majority of the individuals are living in an urban area (64 per cent) and attending school (54 per cent). Child workers are significantly different from non-child workers in several dimensions. As anticipated, 42 per cent of individuals who worked as children are currently employed whereas only 23 per cent are employed among the group of non-child workers. By the same token, child workers are less likely to continue with education (33 per cent) in comparison to those who were not working (56 per cent). Furthermore, it is also apparent that the child workers are from poor households as shown by variables such as per capita expenditure and household characteristics. Interestingly, there is a statistical difference between child workers and non-child workers in terms of their body mass index. Specifically, 13 per cent of those who worked as children are obese compared to eight

[16] According to WHO (2000), the proposed classification of weight by BMI in adult Asians is; underweight ($\prec$18.5 kg/m^2), normal range (18.5 - 22.9 kg/m^2), overweight (23.0 - 24.9 kg/m^2) and obese ($\succcurlyeq$25kg/m^2).

per cent of the non-working group. Moreover, the proportion of underweight individuals are low among child workers (20 per cent), while 30 per cent of non-child workers are underweight during their adolescence age.

Figure 3.1: Distribution of mental health score of child workers and non-child workers



Note: This figure is based on data from IFLS 4 (2007) and IFLS 5 (2014) waves. Higher CES-D score reflects more pronounced depressive symptoms.

3.5 Methodology

3.5.1 Identification Issues

From an empirical viewpoint, identifying the causal effect of child labour on long-term mental health is challenging due to several factors leading to endogeneity. First, it is possible to have a two-way causal relationship between the likelihood of working and the health status of the child resulting in simultaneity. Particularly, child labour inevitably leads to a 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 determines whether the child is capable of working. Healthier children - both physically and mentally - are more likely to be productive and, thus, engage in labour market activities. The former suggests a negative association between child work and health, whereas the latter suggests a positive association between child's health and the likelihood of working.

Second, omitted variables such as genetic health endowments and preferences of parents can influence both the decision to work and health status. O'Donnell et al. (2005) assert that 'healthy worker selection effect' and 'preference effect' arise due to such unobservable heterogeneity. Since health and labour productivity are positively related, the children who are inherently healthy due to unobserved genetic health endowments are more likely to be employed in work activities (O'Donnell et al., 2005). This means the 'healthy worker selection effect' induces a positive relationship between child health and work status. On the other hand, the preference effect refers to the preferences and attitudes of parents in relation to their children. For instance, parents who are more concerned about the wellbeing of their children are less likely to engage them in any type of market work. Besides, they are also likely to allocate more resources to improve the child's health. Therefore, the preference effect suggests that child health and work status can be negatively related (O'Donnell et al., 2005).

Third, selection bias can also lead to endogeneity. Beegle et al. (2009), identify two sources of selection bias: between-household selection and within-household selection. The types of households which are more likely to have child labour is referred to as between-household selection (Beegle et al., 2009). For instance, children in poor households are more vulnerable for child labour (Basu & Van, 1998; Edmonds, 2007; ILO, 2017). On the other hand, poverty and poor health are inextricably linked, where poverty can be identified as both a cause and consequence of poor health. Hence, between-household selection indicates an adverse relationship between child work and health. Within-household selection refers to the parent's choice on selecting which of their children should be sent out to work (Beegle et al., 2009) and is quite similar to preference effect suggested by O'Donnell et al. (2005). It is more likely that parents select those children who are more productive and have higher returns to labour market activities (Horowitz & Wang, 2004). An individual's level of productivity depends on several unobservable traits such as ability and resilience to strenuous tasks which can also have an impact on mental health. Therefore, it is apparent that such within-household selection could also lead to biased estimates.

3.5.2 Identification Strategy - Instrumental Variable (IV) Framework

Given the endogenous nature of child labour on mental health, the use of Ordinary Least Squares (OLS) would lead to biased results. The common approach to address such endogeneity bias of child work is through an instrumental variable (IV) framework. When considering similar studies on physical health effects of child labour it is possible to identify 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 & Maliki, 2008), migrant ratio (O'Donnell et al., 2005), dependency ratio (Kana et al., 2010), local adult employment rate (Wolff & Maliki, 2008), rainfall (Trinh, 2020) and minimum wage (Sim et al., 2017), although the validity of some are questionable.

Based on the context of our study, we consider two potential instruments: the minimum wage proposed by Sim et al. (2007) and the number of family-owned businesses by the household.[17] An ideal instrument is one that induces variation in child labour exogenously (relevance) and affects the outcome of interest (mental health) only through child labour (exclusion restriction).[18] Therefore, we consider these two conditions of relevance and exclusion restriction for each of the instruments in turn.

3.5.2.1 Minimum Wage

According to Sim et al. (2007), adult minimum wage affects the supply of child labour. Their argument is built on the theoretical model proposed by Basu (2000), which shows that a higher minimum wage can have either a positive or a negative effect on child labour. Since child labour occurs due to household vulnerabilities connected with poverty (Basu & Van, 1998), a higher minimum wage would lower child labour through improved income and living conditions. However, according to Basu (2000), 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 non-existent, which compels the unemployed

[17] Given that our outcome of interest (mental health), we believe instruments such as price of rice, school quality, migrant ratio, dependency ratio and rainfall are not valid instruments due to potential violation of exclusion restriction.

[18] Put differently, there should be no correlation between the IV and any other determinants of the dependent variable (Angrist & Pischke, 2009).

parents to send their children to work. In the context of Indonesia, Magruder (2013) provides strong evidence that a minimum wage increase, in fact, leads to an increase in formal employment while decreasing informal employment. This means a change in minimum wage can affect the supply of child labour in Indonesia, through changes in formal employment, indicating further support on the relevance of minimum wage on child labour.

Unlike relevance, whether the minimum wage satisfies the exclusion restriction is not straightforward. However, based on the procedure that is followed in calculating the minimum wage in Indonesia, Sim et al. (2017) argue that the minimum wage meets this criterion. The 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). Initially, there was a single minimum wage level for each province, decided by a forum consisting of employers, representatives of employees and the government. From 2001 onwards, the power to set minimum wage levels was decentralised to governors and mayors who are the respective heads of provinces, cities and districts (Suryahadi et al., 2003). This mechanism implies that the minimum wage level is based on province-specific conditions rather than individual specific conditions. Furthermore, the differences between provincial minimum wages capture the fluctuations in prices and the level of bargaining in each province (Sim et al., 2017). Therefore, it is unlikely that the minimum wage will have a direct effect on mental health status.[19]

We follow Sim et al. (2017), in constructing the instrumental variable of minimum wage. For child workers, the minimum wage is matched based on the specific province and year in which they commenced working.[20] For non-child workers, we use their current province of residence. To obtain the year that they would have commenced working, we follow the approach in Sim et al. (2017) and use 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

[19]To further 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 against the average minimum wage for people from that province. Figure B1 in Appendix shows that there is no significant pattern implying no correlation between minimum wage and mental health.

[20]The minimum wage data is obtained from the Indonesian Central Bureau of Statistics (BPS) (15 October 2018). Retrieved from https://www.bps.go.id/linkTableDinamis/view/id/917

Since IFLS 4 does not provide the year in which the child started to work, we calculate it using the age in which the child started to work and the year of birth.

coefficients to predict the starting year for non-workers.

3.5.2.2 Number of Family Owned Businesses

As our second instrument, we select the number of family-owned businesses (such as trade/retailing) operated at any time during the year 2007 as a potential IV for child work (in 2007). This selection is based on studies such as Kana et al. (2010) and O'Donnell et al. (2005) which consider household land holdings as an instrumental variable.

Regarding the instrument relevance, the number of business owned by the household is a plausible determinant of child work.[21] Increase in the number of businesses would inevitably lead to increased child work activity as it is certainly cost-effective to employ family members including children. This is because most of the economic work conducted by family members are unpaid. Considering the exclusion restriction, there is a potential threat that this could be possibly violated. The number of family business can have a direct effect on the mental health of children through improved living standards. However, we address this issue by including household income and other poverty proxies as control variables in our estimating equation. According to O'Donnell et al. (2005), controlling for all else, the number of family-owned businesses would not affect the health of children, particularly after a period of seven years. This suggests the validity of using it as an instrument for child work.

3.5.3 Estimation Equation

To identify the long-term mental health impact of child work we estimate the following two-stage model:

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

and

[21] We acknowledge that child work in family business has a gendered behaviour - girls are more likely to contribute to housework and boys are more likely to join family business at a young age (Webbink et al., 2012).

$$CL_{i,2007} = \gamma + \delta\mathbf{Z}'_{it} + \psi\mathbf{X}'_{i,2014} + \vartheta\mathbf{P}'_{i,2007} + \varphi_{i,2014} + \upsilon_{i,2007} \qquad (2)$$

where equations (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 $CL_{i,2007}$, which is a dummy 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. $\varphi_{i,2014}$ denotes the provincial fixed effects and $\varepsilon_{i,2014}$ is the error term. $\mathbf{Z}_{it}$ is the matrix of instruments (the minimum wage is observed in the actual/imputed year t in which the individual i began/would have begun working and the number of family owned businesses of individual i is observed in 2007).

3.5.4 Empirical Model

Considering the nature of our main outcome variable of interest (mental health score based on CES-D scale), we employ a Poisson model to estimate the effect of child work on mental health, conditional on the set of covariates mentioned in section 3.4.3. Although the mental health score is not a natural count per se, it exhibits other important characteristics of count data such as non-negative integer-values, a limited number of discrete values and heteroskedastic data skewed to the right. In such instances, Poisson regression is considered as a better alternative to linear regression (Cameron & Trivedi, 2005).[22]

One of the restrictions of using PRM to model count data is its assumption of equidispersion. In the case of overdispersion (that is, variance greater than the mean), the conditional mean should be correctly specified to obtain a consistent Poisson MLE. According to Cameron and Trivedi (2009), the use of robust estimate of variance-covariance matrix (VCE) could also model the feature of overdispersion of the data. Due to the endogenous nature of our main independent variable of child work, we

[22]See Cameron and Trivedi (2009), for a detailed explanation of the poisson regression model (PRM).

apply instrumental variable poisson model (IV-Poisson) based on generalised method of moments (GMM) approach.[23]

3.6 Empirical Results

3.6.1 First-stage Estimates

We begin our empirical analysis with first stage regressions as it provides important diagnostic tools to assess the validity of the selected instrumental variables. To account for heterogeneous nature of child work, we estimate three separate equations for three different outcomes: (1) whether the child worked in any economic activity, (2) worked for wages only and (3) worked in family business. Table 3.1 reports the first stage estimates. Panel A shows the first stage results of the overidentified model. Both minimum wage and the number of family-owned businesses are statistically significant determinants of child work in any economic activity (column 1). The Kleibergen-Paap F-statistic of 21.43 suggests both are strong instruments.[24] Additionally, based on the p-value of the Hansen's test, it can be inferred that the overidentifying restriction is valid.

Considering the child work for wages (column 2), it is evident that the number of family-owned businesses is not a significant determinant of wage work at conventional levels. This is also reflected by the Kleibergen-Paap F-statistic of 9.18, indicating that the instruments are weak. A similar result is also apparent for child work in family enterprises where minimum wage is not a strong IV. Therefore, we re-estimate the first stage regressions considering only minimum wage as an IV for wages equation and number of family-owned business as an IV for family work. Panels B and C present the results. The F-statistics of both panels (17.923 and 31.129) indicate that minimum wage is a strong IV for wage work, whereas number of family-owned businesses is a strong IV for family work.

[23]We use the ivpoisson command in Stata/SE 15

[24]In contrast to the Cragg-Donald F test, the Kleibergen-Paap F-statistic does not assume that the standard errors are *iid* when identifying weak instruments.

Table 3.1: First Stage Estimation Results

	(1) Both	(2) Wages	(3) Family
Panel A			
Minimum wage	0.048***	0.027***	0.021
	(0.014)	(0.006)	(0.013)
Number of family owned businesses	0.039***	0.001	0.038***
	(0.007)	(0.002)	(0.007)
Underidentification test - Kleibergen-Paap LM Statistic	41.772	18.311	32.882
Underidentification test - P-value	0.000	0.000	0.000
Weak identification test - Kleibergen-Paap F Statistic	21.430	9.176	16.788
Overidentification test - Hansen J statistic	0.389	0.716	1.462
Overidentification test - P-value	0.533	0.398	0.227
Panel B			
Minimum wage		0.027***	
		(0.006)	
Underidentification test - Kleibergen-Paap LM Statistic		17.923	
Underidentification test - P-value		0.000	
Weak identification test - Kleibergen-Paap F Statistic		18.018	
Panel C			
Number of family owned businesses			0.038***
			(0.007)
Underidentification test - Kleibergen-Paap LM Statistic			31.129
Underidentification test - P-value			0.000
Weak identification test - Kleibergen-Paap F Statistic			31.613

Notes: The Stock-Yogo critical values for 10%, 15% and 20% maximal IV size are 19.93, 11.59 and 8.75 respectively for the overidentified model (Panel A). The respective values for Panel B and C are 16.38, 8.96 and 6.66. All regressions include the full set of control variables denoting socio-demographic factors, income proxies, adverse and stressful events, religiosity, social capital, health status, habits and behavioural factors as given in Appendix Table B2.

Following the first stage estimation results, it is noteworthy to discuss why minimum wage is a strong IV for working for wages, whereas the number of family-owned business is a strong IV for family work.

The minimum wage was first introduced in 1989 with the objective of regulating the labour market in Indonesia. In general, minimum wages are deemed to cover workers in the formal sector who work 40 hours per week (or 7 to 8 hours per day) (Chun and Khor, 2010). As proposed by Basu (2000), if a rise in the minimum wage causes adult unemployment to rise, then the demand for child labour could increase, since child labour does not fall within the purview of formal employment. This is because of two reasons; (1) most of the child workers are employed for less than 40 hours per week or 8 hours per day; (2) according to the Indonesian Manpower Act, it is illegal to employ child workers as the minimum age for employment is set at 15 years and for hazardous work at 18 years. This means there is a higher tendency that the child workers are paid a lower wage than that of prevailing market or minimum wage levels. Therefore, a considerable change in minimum wages could possibly lead to a change in the demand and supply of child labour for wages.

Regarding family work (both farm and non-farm) in Indonesia, most of these are performed by family members for which there would be no payment. To justify this, we assess if the type of employment undertaken by parents differ by whether or not a child has worked for the family business.[25] Table 3.2 shows that among the children who work for family business, 42 per cent have mothers who are unpaid family workers. Furthermore, 54 per cent have fathers who are self-employed with temporary workers. These statistics imply that child work in family business are usually unpaid and thus might not be affected by changes in statutory wage rates but by factors such as the number of businesses owned by the household. Therefore, based on our first stage estimation results and the above discussion, it can be argued that the type of instrument to be employed also depends on the nature of the work activity.

Table 3.2: Descriptive statistics of parent's employment types

Variable	Family work = 1		Family work = 0		
	Mean	SD	Mean	SD	Difference
Mother unpaid family worker	0.42	0.49	0.18	0.39	0.24***
Father unpaid family worker	0.04	0.19	0.02	0.12	0.02**
Mother self employed with temporary workers	0.30	0.46	0.10	0.29	0.20***
Father self employed with temporary workers	0.54	0.50	0.24	0.43	0.30***
Mother self employed with permanent workers	0.01	0.11	0.01	0.09	0.00
Father self employed with permanent workers	0.03	0.17	0.02	0.14	0.01

Notes: Mean difference is the difference of means between child workers and non-child workers for each of the variables. *** p<0.01, ** p<0.05, * p<0.1.

[25]The IFLS does not provide comprehensive details regarding the type of family work performed by children.

3.6.2 The Effect of Child Work on Mental Health

Having established the validity of the instruments, we first estimate the effect of child work in any economic activity on mental health using both minimum wage and number of family-owned business as instruments. Panel A of Table 3.3 presents the estimation results. In all estimations the standard errors are clustered at both household and province levels to correct for heteroscedasticity and intra-household correlations since we observe more than one child for 25 per cent of the households in our sample. As a benchmark, we also report the ordinary least squares (OLS) and two-stage least squares (2SLS) estimates. It is evident that in all these estimations, the coefficient of child work is positive as expected.[26] The estimated coefficients from both OLS and Poisson models are small and statistically not significant from zero. As indicated earlier, these OLS and Poisson estimates that ignore the problem of endogeneity might be biased. For the 2SLS and IV-Poisson results that take into account the endogeneity, we find that the estimated coefficients are large and statistically significant. However, considering the nature of our outcome variable, we consider IV-Poisson to be a better fit than 2SLS (Linear IV) model and therefore interpret its coefficients.

Column 4 of Panel A shows that, on average, child work in any economic activity leads to a significant increase in mental health score (based on the CES-D scale). We find that working as a child increases adolescence CES-D score by approximately three points which is statistically significant at 5% level. Given the sample mean of 7.5, this translates into a 40 per cent increase in mental health score. Moreover, this pushes the average score among the child workers to exceed the cut-off of 10, suggesting clinically depressive symptoms.[27]

[26] We report the marginal effects for Poisson and IV-Poisson models.

[27] These results are interpreted in relation to the average mental health score of the total sample.

Table 3.3: The effect of child work on mental health

	(1)	(2)	(3)	(4)
	OLS	2SLS	Poisson	IV-Poisson
Panel A				
Child work - Both	0.378	3.534*	0.372	3.003**
	(0.287)	(1.910)	(0.279)	(1.432)
Observations	3,839	3,839	3,839	3,839
R-squared	0.150	0.119		
Panel B				
Child work - Wages	0.377	8.592*	0.394	5.875**
	(0.764)	(4.996)	(0.723)	(2.588)
Observations	3,839	3,839	3,839	3,839
R-squared	0.150	0.119		
Panel C				
Child work - Family	0.385	2.477	0.370	2.320
	(0.305)	(2.690)	(0.296)	(2.131)
Observations	3,839	3,839	3,839	3,839
R-squared	0.150	0.138		

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis, clustered at household and province levels. The marginal effects for Poisson and IV-Poisson models are reported. All estimations include province fixed effects and full set of variables. See Tables B4 and B6 for comprehensive results.

Next, we examine whether long-term mental health effects vary based on the type of child labour, that is whether the child has worked for wages or for family work. Panel B of Table 3.3 presents the estimation results derived for child work for wages using only minimum wage as an IV as discussed in section 3.6.1. Similar to working in any economic activity, OLS and Poisson estimates of working for wages are small and statistically not significant from zero indicating the problem of endogeneity. Both 2SLS and IV-Poisson estimates which account for endogeneity clearly show that working as a child for wages leads to a significant increase in mental health score (CES-D score). Compared to previous estimates of any type of child work (see Panel A), the magnitude of the effect of wage work is substantial. Specifically, working for wages increases the CES-D score by approximately 5.9 points (column 4). Considering the sample mean of 7.5, this translates into a 79 per cent increase in mental health score. This also pushes the average score well above the cut-off of 10, indicating the presence of significant depressive symptoms. Though the estimated effect is large, it is consistent with previous studies on early life circumstances/adversity and long term mental health. We interpret these results in detail in Section 3.8.

Panel C of Table 3.3 provides the estimation results derived for child work for family enterprises using the number of family-owned businesses by the household as an instrument. It is evident that the coefficient of child work for family businesses is statistically insignificant at conventional levels in all estimations. This means there is no significant impact of working as a child in family enterprises on adolescent mental health.

Taken together, child labour has a significant impact on the child's long-term mental health status. The effect is heterogeneous, where children who work for wages are more likely to be affected by depression, whereas working as a child in family enterprises does not lead to significant mental health effects. This implies that child work for wages is a worse form of child labour.[28]

3.6.3 The Effect of Other Covariates on Mental Health

Table B4 in Appendix reveals important insights in relation to determinants of adolescent mental health. We also test for joint statistical significance of subsets of covariates and the results are presented in Table B5 in Appendix. In line with previous literature on mental health, demographics, childhood adversity, religiosity and physical health status are jointly statistically significant at the 0.01 level. Under demographic factors, we find that women's mental health score is 0.8 points higher than male, whereas being married reduces the score by approximately one point.

Interestingly, experience of adverse events as a child is associated with a higher level of depression in adolescence. Individuals who reported to have fair or poor health during childhood are more likely to have depression as an adolescent where the score increases by 0.6 points. Similarly, being exposed to hunger as a child is associated with approximately one point increase in mental health score. Considering the average mental health score, this equates to an effect of 13 per cent increase which is substantial. Though these effects correspond to correlations rather than causations, they imply that experience in childhood adversity is an important determinant of adult mental health status. Given

[28]These results are consistent even if we use an indicator variable to denote depression. See Table B7 for estimation results.

that child labour in itself is also a type of childhood adversity, these findings justify as to why working as a child could have a significant impact on adolescent mental health.

Consistent with previous studies such as Koenig et al. (2012), it is also shown that being religious decreases the mental health score or depressive symptoms by 0.6 points. Moreover, individuals who are more generous in terms of willingness to help others are less likely to be depressed where the mental health score decreases by approximately 1.6 points.

Table B4 also highlights the strong relationship between physical and mental health. This is also established by the joint test of significance of the health status measures as they are jointly statistically significant (see Column 4 of Table B5). On average, individuals who self-reported to be healthy have a significantly lower CES-D score meaning they are less likely to be depressed. Similarly, an increase in the number of chronic conditions or acute morbidities is associated with a higher CES-D score. In line with Liew (2012) and Scheffel and Zhang (2018), these findings clearly indicate that a deterioration of physical health leads to poor mental wellbeing. Interestingly, these results also uncover a potential channel through which child labour could affect mental health. As discussed in Section 3.3, child labour has an adverse impact on short and long-term physical health (Guarcello et al., 2004; O'Donnell et al., 2005; Sim et al., 2017). This implies that physical health could be a possible mechanism in which child labour affects adolescent mental health. Specifically, working as a child leads to poor physical health which in turn affects mental health status.

3.6.4 Mediating Factors

We find that working as a child results in higher depressive symptoms as an adolescent. Understanding the factors that could mediate this substantial effect is important in drawing policy insights to protect children and adolescents from enduring consequences of child labour. In this regard, we consider two potential mediating factors - religiosity and social capital (as proxied by the level of participation in community activities), based on psychological literature and the availability of data.

The impact of religion on mental health has been highlighted in several studies (see Koenig et al. 2012). Involvement in religious activities can be either a preventive or a coping mechanism of emotional distress and depression (Koenig & Larson, 2009; Levin, 2010), thus leading to better mental health. According to Koenig and Larson (2009), there are three possible channels of which religion can modulate psychological disorders. First, religious beliefs and practices make a person more optimistic about life by providing a sense of direction and purpose. Second, most religions advocate outward-directed behaviours such as compassion, kindness and generosity. Being supportive and caring for one another is an integral part of any religion. Such favourable emotions and traits, in turn, could help a person to distract from his/her own problems or distress. Third, engaging in religious activities also enhance social networks. Presence of supportive relationships, especially during the times of stress plays a crucial role in dealing with it (Koenig & Larson, 2009). The association between religiosity and mental wellbeing is also established in empirical research where it is shown that depression patients who receive religious interventions are more likely to recover quickly compared to those who do not (Koenig, 2001).

Social capital which usually refers to the network of relationships among people in a society is generally shown to be inversely associated with mental disorders (Johnson et al., 2017; Tampubolon, 2012). Empirical research suggests adolescents with either wider social networks with many friends (Rotenberg et al., 2004) or quality networks with friends who share similar beliefs and values (Beiser et al., 2011) are less likely to be affected by psychological distress. This means taking an active part in community activities could be a mitigating factor of depression as it provides an opportunity to develop supportive relationships.

To examine the relative importance of these two mediating factors, we estimate separate regressions by the level of religiosity (i.e. religious and not religious) and involvement in community activities (i.e. active participation and low participation).[29] We choose separate regressions for two reasons. First, we do not have valid instruments to estimate a regression with interacted terms. This is because, apart from child labour, the interaction

[29]Religious subsample includes those who have reported to be very religious and somewhat religious. The remaining sample is identified as not religious.

The average score of participation in community activities is considered as the cut-off to define active and low involvement. We do this to preserve an adequate sample size for each of the subsamples.

term between child labour and the mediating factor is also endogenous. Second, the use of only interaction term in regression imposes strict restrictions, that is, child labour and mediating factor have no independent effect on mental health. However, the limitation of having separate regressions is that there is no formal test to check the significance of the difference between the two regressions. Nevertheless, we believe this would provide some indicative evidence of factors that are likely to play a role in mediating the effect of child labour on mental health.

Table 3.4 reports the results.[30] We find that working as a child for wages leads to a significant increase in mental health score (CES-D score) among those who are reported to be not religious. The estimated effect is large compared to that of the full sample (column 5). Interestingly, there is no statistically significant effect of child work on those who are religious. Similarly, in terms of low and active participation in community activities, we find a statistically significant effect of child work in the sample of those with a low level of participation. On the contrary, those with active participation have a lower, statistically insignificant effect. Overall, the results presented in Table 3.4 suggest that religiosity and social capital are potential mediating factors. More specifically, being religious or involving in community activities could subdue the adverse long-term effects of child labour on mental health.

[30]These IV-Poisson estimations are derived only for working for wages using minimum wage as an instrument since the effect of family work on mental health is insignificant.

Table 3.4: Mediating factors: Effect of religiosity and social capital

	Religiosity		Community Participation		Original Specification
	(1)	(2)	(3)	(4)	(5)
	Not Religious	Religious	Low	Active	Full Sample
Child work-wages	8.487*	4.614	9.064**	2.439	5.875**
	(4.890)	(3.297)	(4.126)	(3.953)	(2.588)
Sample means	7.91	7.24	7.48	7.44	7.46
Observations	1,254	2,585	2,081	1,758	3,839
IV diagnostics					
Weak identification test - F-stat	7.034	11.848	6.451	13.393	18.018
Under identification test - LM stat	7.285	11.923	6.512	14.362	17.923
Under identification test - P-value	0.007	0.001	0.011	0.000	0.000

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis, clustered at household and and province levels. The Stock-Yogo critical values for 15%, 20% and 25% maximal IV size are 8.96, 6.66 and 5.53 respectively. The marginal effects are reported. See Table B8 for comprehensive results.

3.7 Robustness Checks

3.7.1 Alternative Definition of Child Labour

The empirical results discussed in Section 3.6 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 a 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 3.5 presents the marginal effects derived from the IV-Poisson estimations where Columns 1, 2 and 3 report the results of ever work participation in any economic activity, wage work and family work respectively. In line with the preceding analysis, we use both minimum wage and the number of family-owned businesses as IVs to estimate the effect of child work in any economic activity, whereas estimations for wage work and family work are derived using the strong instrument. The results are similar to those reported in Section 3.6, indicating that the effect of child work for wages on mental health is robust to the choice of child labour definition.

Table 3.5: The effect of child work on mental health - Alternative definition

	(1)	(2)	(3)
	Both	Wages	Family
Child work - wages	2.781**	5.540**	2.265
	(1.329)	(2.559)	(2.097)
Observations	3,839	3,839	3,839
IV diagnostics			
Underidentification test - Kleibergen-Paap LM Statistic	46.512	16.330	31.538
Underidentification test - P-value	0.000	0.001	0.000
Weak identification test - Kleibergen-Paap F Statistic	23.808	16.578	32.060

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include province fixed effects and full set of control variables. The Stock-Yogo critical values for 10%, 15% and 20% maximal IV size are 19.93, 11.59 and 8.75 respectively for the overidentified model (Column 1). The respective values for Columns 2 and 3 are 16.38, 8.96 and 6.66.

3.7.2 Different Model Specifications

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 3.6 reports the results.[31] In specification 1, we exclude all the control variables except the demographic covariates (Column 1). It is evident the coefficient of child work is higher compared to our original specification and is significant at 1% level. In specification 2, we exclude only the childhood adversity controls since factors such as whether the child has experienced hunger or the health status during childhood can be highly correlated with working as a child and might lead to endogeneity. However, Column 2 shows that the exclusion of those does not affect our results. In specification 3, we exclude variables that proxy for the physical health status due to the same concern of endogeneity. Nevertheless, our results are robust and are similar to that of the original specification in column 4.

[31]These IV-Poisson estimations are derived only for child work for wages using minimum wage as an instrument since the effect of family work on mental health is insignificant.

Table 3.6: Robustness checks with different model specifications

Variables	Specification 1 (1) Marginal Effect	Specification 2 (2) Marginal Effect	Specification 3 (3) Marginal Effect	Original Spec. (4) Marginal Effect
Child work - wages	6.545***	6.019**	5.812**	5.875**
	(2.329)	(2.614)	(2.593)	(2.588)
Constant	1.498***	1.948***	1.814***	1.923***
	(0.532)	(0.522)	(0.520)	(0.517)
Demographic controls	Yes	Yes	Yes	Yes
Childhood adversity	No	No	Yes	Yes
Stressful life events	No	Yes	Yes	Yes
Religiosity/social capital	No	Yes	Yes	Yes
Physical health status	No	Yes	No	Yes
Behavioral controls	No	Yes	Yes	Yes
Observations	3,985	3,839	3,839	3,839

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include province fixed effects.

3.7.3 The Effect on Short-term Emotional Wellbeing

To establish the CES-D as a validated measure of mental health, we examine the impact of child labour on various emotions that are closely related to depression. These emotional health indicators are derived from the questions regarding to what extent an individual felt each of the feelings in the day prior to the interview. The responses are based on a scale ranging from 1 to 5; 1 = not at all; 2 = a little; 3 = somewhat; 4 = quite a bit; 5 = very much. As the questions focus on how the individual felt the day before, these indicators can be considered to represent the short term emotional wellbeing of individuals in contrast to CES-D scale which is more of a general measure of long term emotional wellbeing (Scheffel and Zhang, 2018).

Table 3.7 reports the results. Working as a child for wages aggravates the feelings of worry, boredom and anger, which are in fact related with depressive symptoms. Columns 1, 2 and 4 show that, on average, child work for wages leads to an increased risk of developing these negative emotions by 35 to 40 per cent. These effects on related emotions are consistent with the effect of wage work on depression and also reveals the nexus between short-term and long term emotional wellbeing of individuals.

Table 3.7: Child labour effect on emotions

Variables	(1) Worried	(2) Bored	(3) Happy	(4) Angry	(5) Lonely	(6) Tired
Child work - wages	1.856***	2.133***	-1.472	2.005***	-0.194	1.642*
	(0.611)	(0.736)	(1.955)	(0.589)	(1.419)	(0.923)
Mean of the dep. var	1.78	1.93	3.48	1.66	1.67	2.72
Observations	3,839	3,839	3,839	3,839	3,839	3,839

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include province fixed effects and full set of control variables. See Table B9 for comprehensive results.

3.7.4 Sensitivity to Potential Violations of Exclusion Restriction of the Instrument

One of the key assumptions of a valid instrument is the exclusion restriction, that is, there should be no correlation between the IV and any other determinants of the dependent variable (Angrist & Pischke, 2009). In our empirical analysis, there is a potential threat in which this exclusion restriction could be possibly violated. For instance, it can be argued that a change in minimum wage can affect the living standard of the household, which in turn may affect the child's mental health status. We address this threat by including several control variables that capture the household's socioeconomic status in both past and current periods. Additionally, as a robustness check, we examine the sensitivity of our 2SLS estimates reported in Table 3.3 to violations of the exclusion restriction.[32] In this regard, we follow 'Plausibly Exogenous' estimation proposed by Conley, Hansen and Rossi (2012).

Given that our standard IV model:

$$MH_{i,2014} = \alpha + \beta CL_{i,2007} + \eta \mathbf{X}'_{i,2014} + \varphi \mathbf{P}'_{i,2007} + \gamma MinWage_t + \varepsilon_{i,2014} \quad (3)$$

The IV exclusion restriction holds if $\gamma = 0$. The notion of plausible exogeneity relaxes this condition with the assumption that it is not exactly zero but almost zero. The inference method of β depends on the various forms that γ can take; either the support of γ can

[32]We consider only child work for wages using minimum wage as an instrument since the effect of family work on mental health is insignificant.

be assumed or distributional assumptions of γ can be made. In this study, we consider the union of confidence interval (UCI) approach which is based on the specification of a maximum and minimum prior for γ. In other words, this method takes the support of γ to be an interval $[-\delta, \delta]$ and plot a confidence interval of β versus many different values of δ (Conley et al., 2012).

A change in minimum wage can either have a positive or negative effect on mental health. For instance, an increase in minimum wage may lead to an unemployment of a parent (or parents) (Basu, 2000), which in turn may increase the depression levels of a child. On the other hand, it is also possible that a minimum wage increase can result in lower levels of depression through improved household income status and living standards. Therefore, based on an OLS estimation of equation (3) on various specifications, we consider [-0.2, 0.2] as the possible range that γ could take.

Figures 3.2 and 3.3 present the graphical results considering both 95% and 90% confidence bounds for the coefficient of child work respectively.[33] A qualitative conclusion from Figure 3.2 is that the exclusion restriction is possibly violated, without any significant changes in the mental health estimates. However, at 90% confidence bounds there is still a significant effect of wage work on mental health even when the exclusion restriction is violated (see Figure 3.3). Moreover, both figures depict that the true value of the coefficient on child work is mostly positive, which is consistent with the main empirical results.

Two key points are worth mentioning. First, a main limitation of the UCI approach is that the confidence regions are large (Conley et al., 2012), which is also evident from Figures 3.2 and 3.3. Second, there is a trade-off between the strength and plausibility of instruments. Therefore, in the context of our study, using a strong instrument that does not fulfil the exclusion restriction (Conley et al., 2012) may be preferable.

[33]We use the STATA command plausexog by Clarke (2017)

Figure 3.2: 95% Confidence Bounds

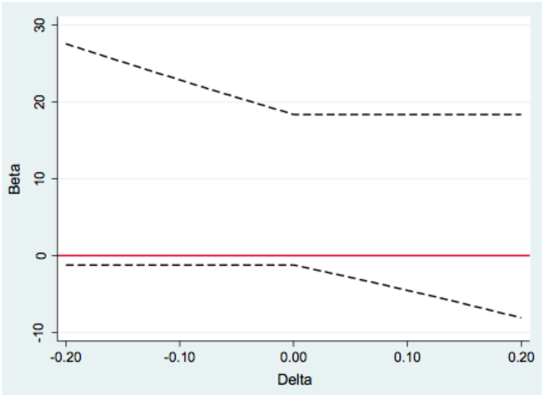
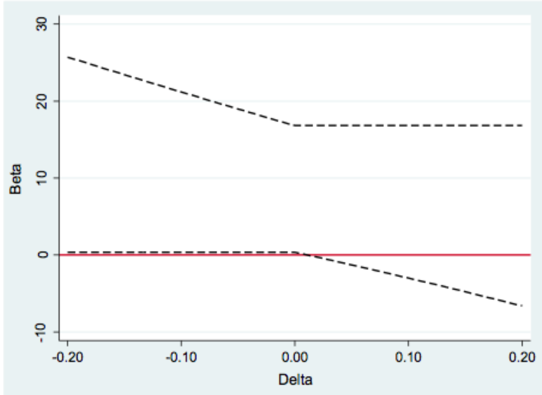


Figure 3.3: 90% Confidence Bounds



Note: Figures 3.2 and 3.3 present 95% and 90% confidence intervals respectively for the estimated coefficient of child work under the assumption that the minimum wage (IV) has a baseline impact on mental health.

3.8 Discussion

Our results show that child labour has negative consequences on mental health. Children who work, particularly for wage work, are significantly more likely to have a higher mental health score or depressive symptoms seven 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.

One common observation in Table 3.3 is that the instrumental variable coefficients are considerably larger in magnitude than the OLS coefficients. This may be due to two reasons. First, the endogeneity factors such as healthy worker effect and preference effect are inducing a downward bias resulting in lower OLS estimates. For instance, as discussed in section 3.5.1, healthier children, both physically and emotionally are more likely to be engaged in labour market activities. This suggests that these children may have higher emotional stability compared to non-child workers, and therefore working as a child may have a minimum impact on their mental health. Second, the instrumental variable estimates are generally referred to as local average treatment effects (LATE). That is, we capture the causal effect of child work for the subgroup of children whose decision to work is affected by the instrument (either minimum wage or number of family business). This subgroup of children is called compliers (Angrist & Pischke, 2009). It is possible that the causal effect for these compliers to be larger than those for the group as a whole. Moreover, this cautions that it is not possible to draw valid inferences on those children whose decision to work is not affected by the selected instrument.

Compared to previous studies examining the effect of early-life circumstances/adversity on long-term mental health (such as Adhvaryu et al., 2018; Gong et al., 2017; Singhal, 2018), the magnitude of our estimated effect for working as a child for wages (which corresponds to an increase in CES-D score by 79 per cent of the mean) is not contradictory. For example, Singhal (2018) finds that one per cent increase in bombing during childhood (as a result of the American war in Vietnam) increases the likelihood of severe depression in adulthood by 50 per cent of the mean based on the same measure of CES-D scale. According to Adhvaryu et al. (2018), one standard deviation increase in cocoa prices in early life reduces the likelihood of severe mental distress among adults in Ghana by 50 per cent of the mean. On the other hand, Gong et al. (2017) find strikingly large effects where the send-down experience increases mental disorders by more than 600 per cent of the control mean. Notably, all these studies focus on very long-term consequences, that is the effect of childhood adversity on adult mental health after 30 to 40 years. Given that our study focuses on the effect of child labour on mental health only after seven years, it is justifiable to have a considerably larger effect.

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 (Fasa, 2003). In the context of Indonesia, child labour is mostly used in the industries of footwear (sandals), gold, palm oil, rubber, tin and tobacco (US Department of Labour's Bureau of International Labour Affairs, 2018). 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, 2004) than adults. In fact, such health risks could persist into adulthood. Specifically, given that childhood is a vulnerable period in brain development (Alwin & 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.

Departing from previous studies on child labour, we also examine the heterogeneous nature of child work on adolescent mental health. Surprisingly, we find that only wage work has a significant impact on mental health, whereas working as a non-paid family worker does not affect mental health. This may be because compared to wage work, family work is less strenuous where children assist their parents to make ends meet. In other words, our findings suggest that working for wages is a worse form of child labour and thus detrimental to children's mental development. Additionally, we also provide indicative evidence that religiosity and social capital are two factors that could modulate the adverse effect of child labour on mental health.

3.9 Conclusion

Child labour constitutes the violation of the fundamental rights of children, while inevitably leading to adverse consequences on their wellbeing in terms of physical, social, psychological and educational development. 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 impact of child labour on mental health. This paper addresses this empirical gap by examining the causal effect of working as a child on adolescent mental health. To this end, we use longitudinal data from the Indonesia Family Life Survey (IFLS) and employ minimum wage and number of family-owned businesses as instrumental variables to address the endogeneity bias of child work.

The empirical results indicate that child labour has a strong impact on the child's long-term mental health status. Based on the heterogeneity effects of child labour, it is found that working as a child in family enterprises has no impact on adolescent mental health. However, child labour for wages significantly affects mental health after seven years, where the CES-D score increases by approximately 5.9 points. This pushes the average score well above the cut-off of 10 points, suggesting the presence of significant depressive symptoms. The substantial effect of wage work on mental health clearly indicates that wage work is a worse form of child labour which is, in fact, consistent with Sim et al. (2017). We also find that religiosity and social capital play a role in mediating the adverse long-term effects of child labour on mental health.

Our findings point out two key implications. First, the costs of child labour are underestimated. In addition to adverse effects on education and physical health, the consequences of child labour also exacerbate long term mental health problems such as depression. This, in turn, can lead to ripple effects as adolescents with mental health disorders are vulnerable to discrimination, stigma, social exclusion, educational difficulties and risk-taking behaviours (WHO, 2018).[34] Second, from a policy perspective, eliminating worse forms of child labour such as wage work is crucial not only for the psychological wellbeing of adolescents but also for overall economic development. This is because the economic costs of mental illnesses are staggeringly large in less developed countries in terms of productivity and labour market participation (Mathers et al., 2008). Therefore, our results underscore the importance of policy interventions implemented towards eradicating child labour in developing countries.

[34]As cited in World Health Organisation (18 September 2018). Retrieved from https://www.who.int/news-room/fact-sheets/detail/adolescent-mental-health.

Appendix B

Table B1: The 10-item Centre for Epidemiological Studies Depression Scale (CES-D) - Questionnaire

Below is a list of the ways you might have felt or behaved. Please tell me how often you have felt this way during the past week

		During the past week			
		Rarely or none of the time (less than 1 day)	Some or little of the time (1 - 2 days)	Occasionally or a moderate amount (3 - 4 days)	Most or all of the time (5 to 7 days)
1.	I was bothered by things that usually don't bother me				
2.	I had trouble concentrating in what I was doing				
3.	I felt depressed				
4.	I felt everything I did was an effort				
5.	I felt hopeful about the future				
6.	I felt fearful				
7.	My sleep was restless				
8.	I was happy				
9.	I felt lonely				
10	I could not get going				

Scoring: Zero for answers in the first column, 1 for answers in the second column, 2 for answers on the third column and 3 for answers in the fourth column. The scores of questions 5 and 8 are reversed (i.e. 3, 2, 1 and 0 respectively).

Table B2: Variable Description

Variables	Description
Mental health score	The mental health score based on CES-D-10 scale
Child work - wages	=1 if ever worked for wages as a child (past month)
Child work - family	=1 if ever worked in farm or non farm family businesses as a child (past month)
Demographics	
Female	=1 if the individual is a female
Age	Age of the individual
Urban	=1 if the household is in an urban area
Marital status	
Married	=1 if married or cohabiting
Divorced	=1 if divorced, separated or widowed
Unmarried*	=1 if unmarried
Work status	
Employed	=1 if working/helping to get an income
Unemployed	=1 if looking for a job or unemployed
Schooling	=1 if a student
House keeping	=1 if a house keeper
Retired or sick*	=1 if retired, sick or disable
Education	
Education elementary	=1 if the individual has elementary education
Education junior	=1 if the individual has junior education
Education senior	=1 if the individual has senior education
Education tertiary	=1 if the individual has tertiary education
Education none*	=1 if the individual has no/not yet in school
Proxies for contemporaneous income	
lnpce	Logarithm of monthly per capita expenditure in 2014
Dependency ratio	The ratio of the number of household members aged below 14 and above 65 years to the number of working members aged 15 - 64 years in 2014
Toilet river/land/sea	=1 if the household does not have proper toilet facilities in 2014
Cook firewood	=1 if the household uses firewood as the main source of energy for cooking in 2014
Proxies for past income	
lnpce 2007	Logarithm of monthly per capita expenditure in 2007
Dependency ratio 2007	The ratio of the number of household members aged below 14 and above 65 years to the number of working members aged 15 - 64 years in 2007
Toilet river/land/sea 2007	=1 if the household does not have proper toilet facilities in 2007
Cook firewood 2007	=1 if the household uses firewood as the main source of energy for cooking in 2007
Body mass index	
Under weight	=1 if the BMI is less than 18.5 kg/m^2
Over weight	=1 if the BMI index is between 23.0 to 25.0 kg/m^2
Obese	=1 if the BMI index is above 25.0 kg/m^2
Normal weight*	=1 if the BMI index is between 18.5 to 22.9 kg/m^2
Childhood adverse events	
Child health	=1 if the health was fair or poor during childhood
Bedridden	=1 if confined to bed or home for one or more months during childhood
Child hunger	=1 if experienced hunger in childhood
Parent smoke	=1 if any of the parents used to smoke at age 12
Parent alcohol	=1 if any of the parents used to drink heavily at age 12
Parent mental problems	=1 if any of the parents had mental problems at age 12
Parents unmarried	=1 if the parents were no longer married at age 12

Stressful events	
Accident injury	=1 if an injury caused by an accident limits the daily activities
Fall injury	=1 if an injury caused by a fall limits the daily activities
Natural disasters (ND)	=1 if the household has experienced any type of a disaster during the last 5 years
Injuries	=1 if the disaster was severe enough to cause death, injury to household members
Disruption (dis)	=1 if the household has experienced events that caused economic disruptions
Crime	=1 if a household member has been a victim of crime during the past year
Religiosity and social capital	
Religious	=1 if the individual is very religious or somewhat religious
Willing to help	=1 if willing to help people in village if needed
Community participation	The percentage of communities activities participated within the past year out of total number of community activities known to the respondent.
Physical health status	
Chronic conditions	Number of chronic conditions
Acute morbidity	Number of acute morbidities experienced during the last 4 weeks
Self reported health status	=1 if the reported health status is 'healthy'
Days missed	Number of days missed during the last 4 weeks in primary activity due to poor health
Physical activity	
Moderate Activity	Number of days per week engaged in moderate activity
Vigorous Activity	Number of days per week engaged in vigorous activity
Walking Activity*	Number of days per week engaged in walking activity
Habits and behavioral factors	
Smoke	=1 if ever smoked or chewed tobacco
Still smoke	=1 if it is a current smoker
Fruits	=1 if consumed fruits more than 2 days in the last week
Vegetables	=1 if consumed vegetables more than 2 days in the last week
Soft drinks	=1 if consumed soft drinks in the last week
Provincial dummies	Seperate indicator variables for each of the following provinces: North Sumarta, West Sumarta, South Sumarta, Lampung, Jakarta, West Java, Central Java, Yogyakarta, East Java, Bali, West Nusa Tenggara, South Sulawesi and South Kalimantan
Instruments	
Minimum wage	The provincial legislated minimum wage in hundreds of thousand rupiahs
Number of family-owned business	The number of family-owned businesses such as trade/retailing operated at any time during 2007.

Variables marked with * indicates the reference group.

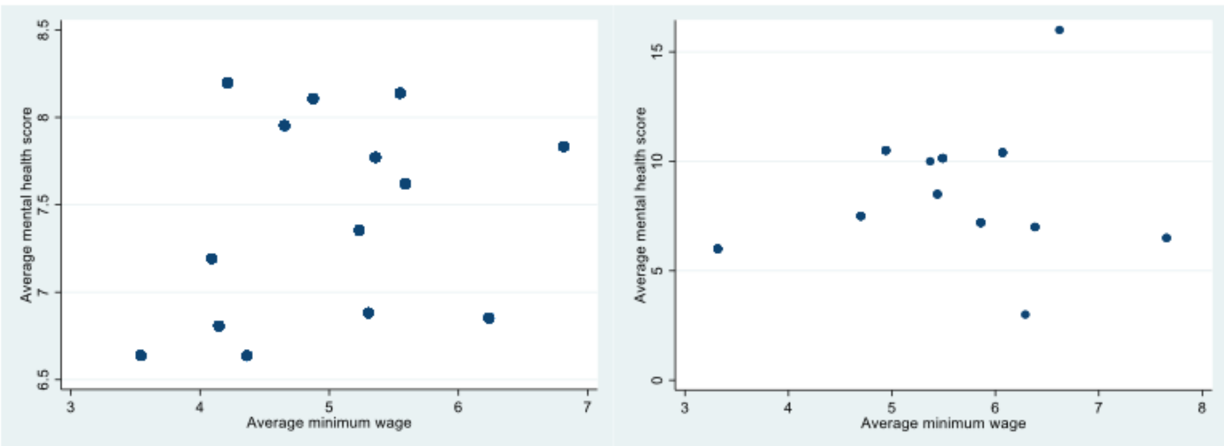
Table B3: Summary Statistics

Variables	Full Sample		Child workers		Non child workers		Mean
	Mean	SD	Mean	SD	Mean	SD	Difference
Mental health score (min=1, max=26)	7.46	4.63	8.08	4.88	7.41	4.60	0.68***
Demographics							
Female (=1)	0.50	0.50	0.51	0.50	0.50	0.50	0.01
Age (min=14, max=24)	17.62	2.06	18.86	1.88	17.51	2.04	1.35***
Urban (=1)	0.64	0.48	0.56	0.50	0.64	0.48	-0.09***
Marital status							
Married (=1)	0.10	0.30	0.16	0.37	0.09	0.29	0.06***
Divorced (=1)	0.01	0.08	0.00	0.05	0.01	0.08	0.00
Unmarried (=1)	0.89	0.31	0.84	0.37	0.90	0.30	-0.06***
Work status							
Employed (=1)	0.24	0.43	0.42	0.50	0.23	0.42	0.20***
Unemployed (=1)	0.11	0.32	0.12	0.32	0.11	0.32	0.01
Schooling (=1)	0.54	0.50	0.33	0.47	0.56	0.50	-0.22***
House keeping (=1)	0.10	0.30	0.11	0.31	0.10	0.30	0.01
Retired or sick (=1)	0.01	0.08	0.01	0.09	0.01	0.08	0.00
Education							
Education Elementary (=1)	0.07	0.26	0.11	0.32	0.07	0.25	0.05***
Education Junior (=1)	0.22	0.42	0.20	0.40	0.23	0.42	-0.03
Education Senior (=1)	0.57	0.50	0.52	0.50	0.57	0.49	-0.06**
Education Tertiary (=1)	0.13	0.33	0.16	0.37	0.12	0.33	0.04**
Education None (=1)	0.00	0.06	0.01	0.08	0.00	0.06	0.00
Proxies for contemporaneous income							
lnpce (min=11, max=17)	13.73	0.75	13.64	0.71	13.74	0.75	-0.10**
Dependency ratio (min=0, max=4)	0.35	0.38	0.33	0.34	0.35	0.38	-0.02
Toilet river/land/sea (=1)	0.07	0.26	0.11	0.31	0.07	0.26	0.04***
Cook firewood (=1)	0.19	0.39	0.26	0.44	0.18	0.38	0.08***
Proxies for past income							
lnpce 2007 (min=10, max=16)	12.81	0.64	12.75	0.63	12.81	0.64	-0.06*
Dependency ratio 2007 (min=0, max=5)	1.07	0.69	1.21	0.83	1.06	0.68	0.06***
Toilet river/land/sea 2007 (=1)	0.18	0.38	0.30	0.46	0.17	0.38	0.13***
Cook firewood 2007 (=1)	0.39	0.49	0.56	0.50	0.38	0.48	0.18***
Body mass index							
Under weight (=1)	0.29	0.45	0.20	0.40	0.30	0.46	-0.10***
Over weight (=1)	0.09	0.28	0.13	0.34	0.08	0.28	0.05***
Obese (=1)	0.11	0.31	0.13	0.33	0.10	0.31	0.02
Normal weight (=1)	0.48	0.50	0.50	0.50	0.48	0.50	0.03
Childhood adverse events							
Child health (=1)	0.32	0.47	0.39	0.49	0.32	0.46	0.08***
Bedridden (=1)	0.06	0.24	0.08	0.27	0.06	0.24	0.02
Child hunger (=1)	0.04	0.18	0.05	0.21	0.03	0.18	0.01
Parent smoke (=1)	0.67	0.47	0.66	0.47	0.67	0.47	-0.01
Parent alcohol (=1)	0.05	0.21	0.11	0.31	0.04	0.20	0.06***
Parent mental problems (=1)	0.00	0.05	0.00	0.00	0.00	0.05	0.00
Parents unmarried (=1)	0.14	0.35	0.13	0.35	0.14	0.35	-0.01
Stressful events							
Accident injury (=1)	0.09	0.29	0.11	0.31	0.09	0.29	0.01
Fall injury (=1)	0.08	0.27	0.06	0.24	0.08	0.27	-0.02
Natural disasters (ND) (=1)	0.21	0.41	0.21	0.41	0.21	0.41	0.00
Injuries (=1)	0.03	0.17	0.03	0.17	0.03	0.17	0.00
Disruption (dis) (=1)	0.18	0.39	0.19	0.39	0.18	0.39	0.01
Crime (=1)	0.06	0.24	0.07	0.26	0.06	0.23	0.01
Religiosity and social capital							
Religious (=1)	0.67	0.47	0.69	0.46	0.67	0.47	0.02
Willing to help (=1)	0.99	0.10	0.99	0.08	0.99	0.11	0.00
Community participation (min=0, max=100)	25.14	27.56	30.85	30.24	24.63	27.25	6.22***

Physical health status							
Chronic conditions (min=0, max=6)	0.33	0.63	0.33	0.62	0.33	0.63	0.00
Acute morbidity (min=0, max=13)	2.84	2.18	2.88	2.26	2.84	2.18	0.04
Health status (=1)	0.87	0.34	0.83	0.37	0.87	0.33	-0.04**
Days missed (min=0, max=28)	1.49	2.85	1.84	3.25	1.46	2.81	0.39***
Physical activity							
Moderate Activity (min=0, max=7)	2.11	2.53	2.41	2.67	2.08	2.52	0.33**
Vigorous Activity (min=0, max=7)	0.66	1.61	0.94	1.94	0.63	1.57	0.30***
Walking Activity (min=0, max=7)	3.08	2.89	3.31	2.95	3.06	2.88	0.25
Habits and behavioral factors							
Smoke (=1)	0.23	0.42	0.25	0.44	0.22	0.42	0.03
Still Smoke (=1)	0.21	0.41	0.24	0.43	0.21	0.41	0.03
Fruits (=1)	0.26	0.44	0.33	0.47	0.26	0.44	0.07***
Vegetables (=1)	0.61	0.49	0.64	0.48	0.61	0.49	0.04
Soft drinks (=1)	0.33	0.47	0.30	0.46	0.34	0.47	-0.04
Instruments							
Minimum wage (min=1, max=9)	4.82	1.18	4.85	1.36	4.82	1.16	0.03
Number of business (min=0, max=5)	0.56	0.74	0.80	0.83	0.54	0.72	0.27***

Notes: Mean difference is the difference of means between child workers and non-child workers for each of the variables. *** p<0.01, ** p<0.05, * p<0.1.

Figure B1: Plot of average mental health score and minimum wage



Panel A: Non-child workers

Panel B: Child workers

Table B4: The effect of child work on mental health

Variables	(1) OLS	(2) 2SLS	(3) Poisson	(4) IV-Poisson
Child work	0.378	3.534*	0.372	3.003**
	(0.287)	(1.910)	(0.279)	(1.432)
Demographics				
Female	0.744***	0.742***	0.792***	0.789***
	(0.175)	(0.175)	(0.180)	(0.183)
Age	-0.016	-0.106	0.054	-0.024
	(0.307)	(0.259)	(0.056)	(0.073)
Age2	0.002	0.003		
	(0.008)	(0.006)		
Urban	-0.304*	-0.265	-0.276	-0.226
	(0.177)	(0.181)	(0.177)	(0.183)
Married	-1.025***	-1.063***	-0.974***	-0.996***
	(0.364)	(0.372)	(0.326)	(0.334)
Divorced	0.742	0.919	0.573	0.829
	(1.208)	(1.244)	(1.040)	(1.117)
Childhood adversity				
Child health	0.610***	0.561***	0.613***	0.574***
	(0.155)	(0.159)	(0.152)	(0.157)
Bed ridden	0.282	0.256	0.238	0.254
	(0.314)	(0.319)	(0.287)	(0.293)
Child hunger	1.241***	1.257***	1.034**	1.055**
	(0.458)	(0.459)	(0.405)	(0.414)
Parent smoke	0.151	0.187	0.173	0.221
	(0.158)	(0.162)	(0.158)	(0.163)
Parent alcohol	0.711*	0.478	0.653*	0.420
	(0.368)	(0.410)	(0.354)	(0.390)
Parent mental problems	0.276	0.442	0.150	0.342
	(1.016)	(1.053)	(0.925)	(0.983)
Parents unmarried	0.369*	0.426*	0.363*	0.410*
	(0.218)	(0.226)	(0.212)	(0.223)
Religiosity and social capital				
Religious	-0.591***	-0.615***	-0.592***	-0.612***
	(0.157)	(0.158)	(0.156)	(0.159)
Willing to help	-1.612**	-1.674**	-1.512**	-1.602**
	(0.815)	(0.828)	(0.760)	(0.789)
Community participation	0.002	0.001	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Physical health status				
Chronic conditions	0.323**	0.338***	0.275**	0.299***
	(0.127)	(0.127)	(0.112)	(0.114)
Acute morbidity	0.429***	0.432***	0.407***	0.410***
	(0.038)	(0.039)	(0.035)	(0.036)
Health status	-1.315***	-1.280***	-1.154***	-1.111***
	(0.241)	(0.246)	(0.222)	(0.229)
Days missed	0.117***	0.101***	0.099***	0.082***
	(0.031)	(0.033)	(0.025)	(0.027)
Work status				
Employed	0.667	0.811	0.570	0.610
	(1.235)	(1.311)	(1.080)	(1.164)
Unemployed	0.307	0.534	0.176	0.291
	(1.237)	(1.315)	(1.065)	(1.158)
Schooling	0.638	0.898	0.524	0.674
	(1.221)	(1.301)	(1.027)	(1.107)
House keeping	0.836	1.241	0.765	1.083
	(1.273)	(1.362)	(1.171)	(1.306)

Education				
Education elementary	1.298	1.403	1.414	1.456
	(1.016)	(1.118)	(1.324)	(1.451)
Education junior	1.343	1.476	1.477	1.549
	(0.965)	(1.068)	(1.225)	(1.347)
Education senior	1.186	1.334	1.263	1.346
	(0.952)	(1.058)	(1.068)	(1.171)
Education tertiary	1.527	1.669	1.746	1.834
	(0.979)	(1.087)	(1.311)	(1.449)
Body mass index				
Underweight	0.183	0.201	0.172	0.189
	(0.162)	(0.164)	(0.163)	(0.167)
Overweight	0.441*	0.293	0.432*	0.313
	(0.240)	(0.264)	(0.242)	(0.259)
Obese	0.045	-0.019	0.058	-0.007
	(0.247)	(0.255)	(0.252)	(0.260)
Proxies for current income				
lnpce	-0.081	-0.034	-0.067	-0.026
	(0.123)	(0.127)	(0.122)	(0.128)
Toilet river/land/sea	-0.112	-0.086	-0.082	-0.067
	(0.318)	(0.328)	(0.307)	(0.320)
Cook firewood	0.122	0.166	0.140	0.194
	(0.221)	(0.227)	(0.224)	(0.233)
Dependency ratio	-0.111	-0.076	-0.100	-0.067
	(0.211)	(0.214)	(0.208)	(0.212)
Proxies for past income				
lnpce 2007	0.027	-0.048	0.027	-0.056
	(0.145)	(0.151)	(0.144)	(0.152)
Toilet river/land/sea 2007	0.067	-0.045	0.039	-0.075
	(0.218)	(0.234)	(0.215)	(0.230)
Cook firewood 2007	-0.127	-0.277	-0.106	-0.256
	(0.190)	(0.213)	(0.190)	(0.212)
Dependency ratio 2007	0.229**	0.176	0.210*	0.164
	(0.116)	(0.124)	(0.108)	(0.116)
Stressful events				
Accident injury	0.221	0.190	0.212	0.192
	(0.256)	(0.259)	(0.233)	(0.238)
Fall injury	0.730***	0.808***	0.673**	0.751***
	(0.280)	(0.287)	(0.262)	(0.278)
Natural disasters	0.091	0.096	0.087	0.102
	(0.190)	(0.190)	(0.188)	(0.191)
Injuries	0.436	0.354	0.362	0.256
	(0.434)	(0.442)	(0.419)	(0.426)
Disruption	-0.022	-0.010	0.001	0.016
	(0.191)	(0.194)	(0.188)	(0.194)
Crime	0.434	0.365	0.435	0.381
	(0.299)	(0.315)	(0.294)	(0.310)
Physical activity				
Moderate activity	-0.007	-0.006	-0.007	-0.005
	(0.030)	(0.030)	(0.030)	(0.030)
Vigorous activity	0.127**	0.118**	0.111**	0.101**
	(0.051)	(0.052)	(0.046)	(0.048)
Habits and behavioral factors				
Smoke	0.530	0.438	0.624	0.538
	(0.527)	(0.542)	(0.520)	(0.540)
Still smoke	0.034	0.218	0.031	0.216
	(0.542)	(0.564)	(0.511)	(0.548)

Fruits	-0.037	-0.124	-0.021	-0.103
	(0.164)	(0.175)	(0.161)	(0.172)
Vegetables	-0.338**	-0.298**	-0.345**	-0.294*
	(0.148)	(0.151)	(0.148)	(0.153)
Soft drinks	0.212	0.235	0.225	0.256
	(0.159)	(0.161)	(0.156)	(0.160)
Constant	6.631	7.841**		
	(4.036)	(3.845)		
R-squared	0.150	0.119		
Observations	3,839	3,839	3,839	3,839

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis, clustered at household and province levels. All estimations include province fixed effects. The marginal effects for estimated poisson models are reported.

Table B5: Joint significance of groups of covariates

	Demographics	Childhood adversity	Religiosity and social capital	Physical health status	Work status	Education
	(1)	(2)	(3)	(4)	(5)	(6)
F-statistic	26.72	29.98	18.89	277.12	3.49	3.94
P-value	0.00	0.00	0.00	0.00	0.48	0.42
	Body mass index	Proxies for current income	Proxies for past income	Stressful events	Physical activity	Habits and behavioral factors
	(7)	(8)	(9)	(10)	(11)	(12)
F-statistic	2.61	0.81	4.47	13.06	5.16	16.42
P-value	0.46	0.94	0.35	0.04	0.08	0.01

Table B6: The effect of work heterogeneity on mental health

Variables	Wage work				Family work			
	OLS	2SLS	Poisson	IV-Poisson	OLS	2SLS	Poisson	IV-Poisson
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Child work	0.377	8.592*	0.394	5.875**	0.385	2.477	0.370	2.320
	(0.764)	(4.996)	(0.723)	(2.588)	(0.305)	(2.690)	(0.296)	(2.131)
Demographics								
Female	0.743***	0.709***	0.791***	0.759***	0.746***	0.753***	0.793***	0.800***
	(0.175)	(0.178)	(0.181)	(0.185)	(0.174)	(0.174)	(0.180)	(0.181)
Age	-0.006	-0.020	0.062	0.034	-0.015	-0.070	0.055	0.005
	(0.313)	(0.279)	(0.056)	(0.059)	(0.308)	(0.280)	(0.056)	(0.081)
Age2	0.002	0.002			0.002	0.002		
	(0.008)	(0.007)			(0.008)	(0.007)		
Urban	-0.308*	-0.295	-0.281	-0.259	-0.305*	-0.285	-0.277	-0.250
	(0.177)	(0.179)	(0.177)	(0.182)	(0.177)	(0.179)	(0.177)	(0.182)
Married	-1.031***	-1.259***	-0.981***	-1.160***	-1.014***	-0.977***	-0.965***	-0.922***
	(0.363)	(0.402)	(0.325)	(0.347)	(0.364)	(0.368)	(0.326)	(0.336)
Divorced	0.726	0.837	0.548	0.675	0.738	0.831	0.568	0.725
	(1.205)	(1.207)	(1.035)	(1.066)	(1.207)	(1.226)	(1.039)	(1.094)
Childhood adversity								
Child health	0.616***	0.607***	0.618***	0.610***	0.611***	0.580***	0.613***	0.586***
	(0.155)	(0.156)	(0.152)	(0.155)	(0.155)	(0.160)	(0.152)	(0.157)
Bed ridden	0.285	0.302	0.238	0.258	0.281	0.261	0.238	0.244
	(0.314)	(0.316)	(0.287)	(0.294)	(0.314)	(0.316)	(0.287)	(0.290)
Child hunger	1.241***	1.272***	1.034**	1.082***	1.240***	1.244***	1.032**	1.037**
	(0.458)	(0.450)	(0.404)	(0.404)	(0.459)	(0.459)	(0.405)	(0.413)
Parent smoke	0.145	0.123	0.166	0.143	0.152	0.179	0.173	0.211
	(0.158)	(0.159)	(0.158)	(0.161)	(0.158)	(0.163)	(0.158)	(0.167)
Parent alcohol	0.733**	0.601	0.676*	0.550	0.715*	0.585	0.656*	0.508
	(0.368)	(0.390)	(0.355)	(0.375)	(0.368)	(0.411)	(0.354)	(0.401)
Parent mental problems	0.260	0.347	0.132	0.223	0.273	0.362	0.146	0.256
	(1.011)	(1.002)	(0.919)	(0.922)	(1.017)	(1.042)	(0.925)	(0.971)
Parents unmarried	0.357	0.261	0.352*	0.247	0.374*	0.437*	0.368*	0.433*
	(0.218)	(0.233)	(0.212)	(0.231)	(0.218)	(0.235)	(0.212)	(0.232)
Religiosity								
Religious	-0.586***	-0.543***	-0.588***	-0.542***	-0.593***	-0.616***	-0.593***	-0.614***
	(0.157)	(0.161)	(0.156)	(0.162)	(0.157)	(0.159)	(0.156)	(0.159)
Willing to help	-1.610**	-1.724**	-1.508**	-1.642**	-1.607**	-1.622**	-1.507**	-1.541**
	(0.814)	(0.815)	(0.759)	(0.781)	(0.815)	(0.818)	(0.760)	(0.774)
Community	0.002	0.002	0.002	0.001	0.002	0.001	0.002	0.001
participation	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Physical health								
Chronic conditions	0.322**	0.342***	0.273**	0.294**	0.321**	0.326***	0.274**	0.284**
	(0.127)	(0.128)	(0.112)	(0.114)	(0.126)	(0.126)	(0.112)	(0.113)
Acute morbidity	0.428***	0.427***	0.406***	0.405***	0.429***	0.431***	0.407***	0.409***
	(0.038)	(0.038)	(0.035)	(0.035)	(0.038)	(0.038)	(0.035)	(0.035)
Health status	-1.319***	-1.313***	-1.159***	-1.159***	-1.316***	-1.296***	-1.155***	-1.127***
	(0.241)	(0.241)	(0.221)	(0.224)	(0.241)	(0.244)	(0.222)	(0.228)
Days missed	0.119***	0.118***	0.101***	0.102***	0.117***	0.107***	0.099***	0.087***
	(0.031)	(0.032)	(0.025)	(0.026)	(0.031)	(0.034)	(0.025)	(0.029)
Work status								
Employed	0.669	1.105	0.586	0.977	0.647	0.633	0.553	0.478
	(1.229)	(1.293)	(1.076)	(1.178)	(1.237)	(1.284)	(1.081)	(1.137)
Unemployed	0.301	0.773	0.184	0.606	0.285	0.314	0.157	0.122
	(1.230)	(1.297)	(1.060)	(1.184)	(1.239)	(1.286)	(1.065)	(1.119)
Schooling	0.627	1.089	0.528	0.923	0.617	0.673	0.507	0.505
	(1.215)	(1.278)	(1.022)	(1.093)	(1.223)	(1.271)	(1.029)	(1.086)

House keeping	0.819	1.505	0.760	1.439	0.805	0.899	0.735	0.782
	(1.267)	(1.362)	(1.165)	(1.367)	(1.275)	(1.324)	(1.170)	(1.236)
Education								
Education elementary	1.267	0.876	1.390	0.955	1.316	1.482	1.434	1.563
	(1.005)	(1.029)	(1.309)	(1.287)	(1.016)	(1.100)	(1.327)	(1.439)
Education junior	1.323	1.234	1.466	1.371	1.346	1.452	1.480	1.532
	(0.955)	(0.949)	(1.212)	(1.205)	(0.966)	(1.035)	(1.225)	(1.311)
Education senior	1.165	1.085	1.251	1.182	1.189	1.301	1.264	1.321
	(0.941)	(0.934)	(1.057)	(1.057)	(0.952)	(1.026)	(1.068)	(1.141)
Education tertiary	1.511	1.538	1.739	1.784	1.526	1.610	1.743	1.780
	(0.968)	(0.959)	(1.298)	(1.301)	(0.979)	(1.048)	(1.311)	(1.402)
Body mass index								
Underweight	0.182	0.203	0.171	0.191	0.182	0.189	0.171	0.177
	(0.162)	(0.163)	(0.163)	(0.166)	(0.162)	(0.162)	(0.163)	(0.165)
Overweight	0.458*	0.438*	0.446*	0.424*	0.439*	0.333	0.430*	0.330
	(0.240)	(0.242)	(0.242)	(0.246)	(0.240)	(0.280)	(0.242)	(0.273)
Obese	0.052	0.049	0.065	0.053	0.045	0.003	0.058	0.014
	(0.247)	(0.253)	(0.252)	(0.259)	(0.247)	(0.253)	(0.251)	(0.259)
Current income proxies								
lnpce	-0.088	-0.111	-0.074	-0.103	-0.080	-0.044	-0.066	-0.029
	(0.122)	(0.126)	(0.122)	(0.127)	(0.122)	(0.131)	(0.122)	(0.131)
Toilet river/land/sea	-0.115	-0.115	-0.086	-0.121	-0.112	-0.096	-0.081	-0.062
	(0.318)	(0.331)	(0.306)	(0.324)	(0.318)	(0.320)	(0.306)	(0.313)
Cook firewood	0.119	0.180	0.136	0.214	0.119	0.135	0.137	0.161
	(0.221)	(0.228)	(0.224)	(0.236)	(0.221)	(0.222)	(0.224)	(0.228)
Dependency ratio	-0.115	-0.102	-0.103	-0.096	-0.111	-0.091	-0.100	-0.081
	(0.211)	(0.212)	(0.208)	(0.212)	(0.211)	(0.213)	(0.208)	(0.211)
Past income proxies								
lnpce 2007	0.036	0.019	0.035	0.015	0.028	-0.016	0.028	-0.024
	(0.145)	(0.148)	(0.144)	(0.149)	(0.145)	(0.155)	(0.144)	(0.157)
Toilet river/land/sea	0.076	-0.033	0.049	-0.043	0.073	0.030	0.045	-0.006
2007	(0.217)	(0.229)	(0.214)	(0.225)	(0.218)	(0.228)	(0.215)	(0.227)
Cook firewood 2007	-0.108	-0.104	-0.088	-0.097	-0.128	-0.233	-0.106	-0.218
	(0.191)	(0.196)	(0.190)	(0.197)	(0.190)	(0.234)	(0.190)	(0.233)
Dependency ratio 2007	0.233**	0.166	0.211*	0.136	0.232**	0.209*	0.213**	0.197*
	(0.116)	(0.127)	(0.109)	(0.123)	(0.116)	(0.121)	(0.108)	(0.112)
Stressful events								
Accident injury	0.226	0.253	0.216	0.250	0.220	0.195	0.211	0.191
	(0.256)	(0.260)	(0.233)	(0.241)	(0.256)	(0.256)	(0.233)	(0.236)
Fall injury	0.724***	0.788***	0.667**	0.749***	0.728***	0.764***	0.669**	0.707***
	(0.279)	(0.281)	(0.262)	(0.270)	(0.280)	(0.283)	(0.262)	(0.272)
Natural disasters	0.092	0.145	0.088	0.140	0.088	0.079	0.085	0.080
	(0.190)	(0.193)	(0.188)	(0.194)	(0.190)	(0.189)	(0.188)	(0.189)
Injuries	0.441	0.323	0.369	0.261	0.442	0.418	0.367	0.326
	(0.435)	(0.471)	(0.420)	(0.453)	(0.433)	(0.428)	(0.418)	(0.417)
Disruption	-0.024	-0.033	-0.000	-0.001	-0.022	-0.010	0.002	0.013
	(0.191)	(0.194)	(0.188)	(0.193)	(0.191)	(0.192)	(0.188)	(0.192)
Crime	0.445	0.517*	0.446	0.525*	0.430	0.368	0.432	0.370
	(0.298)	(0.300)	(0.294)	(0.302)	(0.299)	(0.315)	(0.294)	(0.311)
Physical activity								
Moderate activity	-0.007	-0.010	-0.007	-0.010	-0.007	-0.006	-0.007	-0.005
	(0.030)	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Vigorous activity	0.128**	0.129**	0.112**	0.112**	0.127**	0.121**	0.111**	0.106**
	(0.051)	(0.053)	(0.046)	(0.049)	(0.050)	(0.051)	(0.046)	(0.047)
Habits								
Smoke	0.545	0.622	0.638	0.723	0.526	0.447	0.620	0.533
	(0.526)	(0.523)	(0.520)	(0.526)	(0.527)	(0.538)	(0.520)	(0.537)

Still smoke	0.011	-0.013	0.007	-0.023	0.035	0.158	0.032	0.171
	(0.542)	(0.537)	(0.509)	(0.508)	(0.542)	(0.564)	(0.511)	(0.549)
Fruits	-0.030	-0.085	-0.015	-0.086	-0.035	-0.080	-0.018	-0.060
	(0.163)	(0.169)	(0.161)	(0.170)	(0.164)	(0.174)	(0.161)	(0.170)
Vegetables	-0.341**	-0.302**	-0.348**	-0.294*	-0.339**	-0.320**	-0.346**	-0.319**
	(0.148)	(0.153)	(0.148)	(0.156)	(0.148)	(0.149)	(0.148)	(0.152)
Soft drinks	0.208	0.186	0.222	0.222	0.213	0.235	0.225	0.245
	(0.159)	(0.160)	(0.156)	(0.158)	(0.159)	(0.162)	(0.156)	(0.160)
Constant	6.512	7.077*			6.609	7.276*		
	(4.067)	(3.944)			(4.046)	(3.929)		
R-squared	0.150	0.119			0.150	0.138		
Observations	3,839	3,839	3,839	3,839	3,839	3,839	3,839	3,839

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis, clustered at household and province levels. All estimations include province fixed effects. We report the marginal effects for estimated poisson models.

Table B7: Estimation using a dummy variable to denote depression [1]

	Both	Wage work	Family work
Variables	Depression	Depression	Depression
	(1)	(2)	(3)
Child work	0.310	1.079**	0.050
	(0.192)	(0.539)	(0.270)
Demographics			
Female	0.076***	0.071***	0.076***
	(0.018)	(0.019)	(0.018)
Age	0.001	0.008	0.008
	(0.028)	(0.029)	(0.033)
Age2	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Urban	-0.018	-0.020	-0.021
	(0.018)	(0.018)	(0.018)
Married	-0.088**	-0.114***	-0.084**
	(0.035)	(0.041)	(0.035)
Divorced	0.123	0.120	0.108
	(0.102)	(0.097)	(0.098)
Childhood adversity			
Child health	0.037**	0.041**	0.042**
	(0.016)	(0.016)	(0.016)
Bed ridden	0.042	0.047	0.044
	(0.033)	(0.033)	(0.032)
Child hunger	0.101**	0.104**	0.100**
	(0.044)	(0.044)	(0.043)
Parent smoke	0.025	0.019	0.022
	(0.016)	(0.016)	(0.016)
Parent alcohol	0.032	0.037	0.052
	(0.041)	(0.041)	(0.040)
Parent mental problems	0.061	0.056	0.047
	(0.137)	(0.133)	(0.135)
Parents unmarried	0.007	-0.012	0.002
	(0.023)	(0.024)	(0.023)
Religiosity			
Religious	-0.022	-0.014	-0.020
	(0.016)	(0.016)	(0.016)
Willing to help	-0.070	-0.079	-0.065
	(0.079)	(0.078)	(0.077)
Community participation	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Physical health			
Chronic conditions	0.014	0.015	0.013
	(0.013)	(0.013)	(0.013)
Acute morbidity	0.038***	0.038***	0.038***
	(0.004)	(0.004)	(0.004)
Health status	-0.115***	-0.117***	-0.118***
	(0.025)	(0.025)	(0.025)
Days missed	0.006**	0.008**	0.008**
	(0.003)	(0.003)	(0.003)
Work status			
Employed	-0.037	0.006	-0.052
	(0.107)	(0.112)	(0.111)
Unemployed	-0.043	-0.003	-0.064
	(0.108)	(0.113)	(0.111)

[1] Depression is denoted by a dummy variable which takes on a value of 1 if the CES-D score is 10 and above and zero otherwise. (Andresen et al., 1994)

Schooling	-0.042	-0.007	-0.067
	(0.108)	(0.111)	(0.110)
House keeping	0.000	0.051	-0.037
	(0.114)	(0.121)	(0.115)
Education			
Education elementary	0.064	0.003	0.058
	(0.103)	(0.101)	(0.100)
Education junior	0.092	0.067	0.081
	(0.099)	(0.094)	(0.095)
Education senior	0.075	0.050	0.064
	(0.098)	(0.092)	(0.093)
Education tertiary	0.112	0.101	0.100
	(0.101)	(0.095)	(0.096)
Body mass index			
Underweight	0.003	0.004	0.002
	(0.017)	(0.017)	(0.017)
Overweight	0.018	0.030	0.030
	(0.028)	(0.026)	(0.029)
Obese	0.016	0.022	0.021
	(0.025)	(0.026)	(0.025)
Current income proxies			
lnpce	-0.012	-0.019	-0.015
	(0.013)	(0.013)	(0.013)
Toilet river/land/sea	-0.032	-0.034	-0.034
	(0.031)	(0.033)	(0.030)
Cook firewood	0.016	0.020	0.012
	(0.022)	(0.023)	(0.022)
Dependency ratio	-0.026	-0.028	-0.029
	(0.022)	(0.022)	(0.022)
Past income proxies			
lnpce 2007	-0.014	-0.009	-0.008
	(0.015)	(0.015)	(0.016)
Toilet river/land/sea 2007	0.006	0.002	0.016
	(0.023)	(0.023)	(0.022)
Cook firewood 2007	-0.036*	-0.021	-0.024
	(0.021)	(0.020)	(0.023)
Dependency ratio 2007	0.016	0.013	0.021*
	(0.012)	(0.013)	(0.012)
Stressful events			
Accident injury	-0.020	-0.013	-0.017
	(0.027)	(0.027)	(0.027)
Fall injury	0.041	0.042	0.034
	(0.030)	(0.030)	(0.030)
Natural disasters	0.018	0.025	0.017
	(0.019)	(0.020)	(0.019)
Injuries	0.023	0.016	0.031
	(0.048)	(0.052)	(0.047)
Disruption	-0.000	-0.003	-0.001
	(0.019)	(0.020)	(0.019)
Crime	0.042	0.058*	0.048
	(0.033)	(0.032)	(0.033)
Physical activity			
Moderate activity	0.000	-0.000	0.000
	(0.003)	(0.003)	(0.003)
Vigorous activity	0.010*	0.011*	0.010*
	(0.005)	(0.006)	(0.005)

Habits			
Smoke	0.123*	0.143**	0.130**
	(0.066)	(0.064)	(0.065)
Still smoke	-0.064	-0.086	-0.080
	(0.068)	(0.065)	(0.067)
Fruits	0.001	0.003	0.009
	(0.018)	(0.018)	(0.018)
Vegetables	-0.026*	-0.025	-0.029*
	(0.015)	(0.016)	(0.015)
Soft drinks	0.043***	0.038**	0.041**
	(0.017)	(0.017)	(0.017)
Constant	0.582	0.537	0.479
	(0.393)	(0.406)	(0.422)
Observations	3,839	3,839	3,839
R-squared	0.086	0.057	0.107

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parenthesis, clustered at household and province levels. All estimations include province fixed effects. The above estimates are based on a linear probability model with the same instrumental variables used for empirical results reported in sections 6.1 and 6.2. Note that it is not possible to use IV-probit since IV-probit is based on maximum likelihood estimation, which assumes that the endogenous covariates are continuous. As our main variable of interest (child work) is a discrete endogenous, the use of IV-probit is therefore not appropriate.

Table B8: Mediating factors: Effect of religiosity and social capital

	Religiosity		Community Participation		Original Specification
	(1)	(2)	(3)	(4)	(5)
	Not religious	Religious	Low	Active	Full Sample
Child work	8.487*	4.614	9.064**	2.439	5.875**
	(4.890)	(3.297)	(4.126)	(3.953)	(2.588)
Demographics					
Female	0.865**	0.787***	0.703***	0.766***	0.759***
	(0.353)	(0.221)	(0.258)	(0.286)	(0.185)
Age	-0.004	0.059	-0.012	0.079	0.034
	(0.103)	(0.071)	(0.082)	(0.087)	(0.059)
Urban	-0.705*	-0.092	-0.367	-0.199	-0.259
	(0.361)	(0.210)	(0.265)	(0.260)	(0.182)
Married	-1.754***	-1.005**	-1.403**	-0.891*	-1.160***
	(0.677)	(0.399)	(0.553)	(0.490)	(0.347)
Divorced	1.329	-0.408	0.593	1.266	0.675
	(1.709)	(1.310)	(1.449)	(1.676)	(1.066)
Childhood adversity					
Child health	0.321	0.711***	0.561**	0.634***	0.610***
	(0.289)	(0.191)	(0.219)	(0.234)	(0.155)
Bed ridden	-0.032	0.398	0.500	0.141	0.258
	(0.496)	(0.373)	(0.420)	(0.412)	(0.294)
Child hunger	1.286**	1.110**	1.473**	0.525	1.082***
	(0.646)	(0.546)	(0.616)	(0.512)	(0.404)
Parent smoke	0.403	0.046	0.435**	-0.154	0.143
	(0.290)	(0.195)	(0.221)	(0.246)	(0.161)
Parent alcohol	0.007	0.964**	0.645	0.502	0.550
	(0.775)	(0.480)	(0.735)	(0.469)	(0.375)
Parent mental problems	1.805	-0.933	1.494	-0.174	0.223
	(1.348)	(1.027)	(2.132)	(0.921)	(0.922)
Parents unmarried	0.263	0.280	-0.146	0.627**	0.247
	(0.364)	(0.303)	(0.363)	(0.318)	(0.231)
Religiosity					
Religious			-0.592***	-0.604**	-0.542***
			(0.218)	(0.255)	(0.162)
Willing to help	-4.123***	-0.175	-0.829	-3.205**	-1.642**
	(1.341)	(0.933)	(0.864)	(1.359)	(0.781)
Community participation	0.003	0.001	0.027**	-0.002	0.001
	(0.005)	(0.003)	(0.014)	(0.005)	(0.003)
Physical health					
Chronic conditions	0.575***	0.190	0.262*	0.296	0.294**
	(0.200)	(0.146)	(0.150)	(0.184)	(0.114)
Acute morbidity	0.405***	0.398***	0.468***	0.351***	0.405***
	(0.063)	(0.043)	(0.051)	(0.054)	(0.035)
Health status	-1.062***	-1.152***	-1.020***	-1.188***	-1.159***
	(0.396)	(0.281)	(0.305)	(0.338)	(0.224)
Days missed	0.125***	0.091***	0.134***	0.103***	0.102***
	(0.042)	(0.032)	(0.038)	(0.037)	(0.026)
Work status					
Employed	0.759	1.750	0.381	3.893	0.977
	(1.413)	(1.826)	(1.576)	(3.852)	(1.178)
Unemployed	0.270	1.455	0.492	3.040	0.606
	(1.392)	(1.891)	(1.655)	(3.917)	(1.184)
Schooling	0.570	1.651	0.698	3.176	0.923
	(1.338)	(1.581)	(1.545)	(3.202)	(1.093)

House keeping	2.130	1.873	1.673	3.319	1.439
	(1.863)	(2.054)	(2.054)	(4.109)	(1.367)
Education					
Education elementary	0.202	1.767	-1.275	2.620	0.955
	(1.425)	(1.932)	(1.625)	(1.764)	(1.287)
Education junior	1.275	1.912	-1.163	2.926*	1.371
	(1.343)	(1.762)	(1.644)	(1.571)	(1.205)
Education senior	0.975	1.658	-1.207	2.392*	1.182
	(1.196)	(1.475)	(1.821)	(1.237)	(1.057)
Education tertiary	1.731	2.214	-0.358	2.786	1.784
	(1.502)	(1.887)	(1.700)	(1.708)	(1.301)
Body mass index					
Underweight	0.581*	-0.027	0.365	-0.031	0.191
	(0.308)	(0.201)	(0.226)	(0.247)	(0.166)
Overweight	0.437	0.434	0.688**	0.252	0.424*
	(0.486)	(0.294)	(0.338)	(0.378)	(0.246)
Obese	-0.289	0.209	-0.218	0.191	0.053
	(0.473)	(0.310)	(0.425)	(0.369)	(0.259)
Current income proxies					
lnpce	-0.150	-0.064	-0.198	0.193	-0.103
	(0.241)	(0.149)	(0.162)	(0.214)	(0.127)
Toilet river/land/sea	0.368	-0.299	-0.278	0.092	-0.121
	(0.629)	(0.363)	(0.454)	(0.449)	(0.324)
Cook firewood	0.043	0.197	0.167	0.221	0.214
	(0.414)	(0.285)	(0.353)	(0.324)	(0.236)
Dependency ratio	0.070	-0.282	-0.279	0.117	-0.096
	(0.383)	(0.259)	(0.292)	(0.319)	(0.212)
Past income proxies					
lnpce 2007	0.311	-0.132	0.097	-0.210	0.015
	(0.271)	(0.177)	(0.205)	(0.234)	(0.149)
Toilet river/land/sea 2007	0.092	-0.057	-0.037	0.035	-0.043
	(0.434)	(0.278)	(0.322)	(0.315)	(0.225)
Cook firewood 2007	-0.066	-0.174	0.206	-0.420	-0.097
	(0.397)	(0.241)	(0.270)	(0.295)	(0.197)
Dependency ratio 2007	0.009	0.177	0.175	0.128	0.136
	(0.260)	(0.135)	(0.177)	(0.174)	(0.123)
Stressful events					
Accident injury	1.020**	-0.177	0.550	0.126	0.250
	(0.434)	(0.292)	(0.367)	(0.341)	(0.241)
Fall injury	0.867*	0.653*	0.476	0.705*	0.749***
	(0.493)	(0.333)	(0.368)	(0.392)	(0.270)
Natural disasters	0.140	0.173	0.033	0.173	0.140
	(0.341)	(0.238)	(0.260)	(0.305)	(0.194)
Injuries	-0.556	0.769	-0.560	0.811	0.261
	(0.724)	(0.624)	(0.736)	(0.643)	(0.453)
Disruption	-0.185	0.065	-0.094	0.145	-0.001
	(0.354)	(0.228)	(0.284)	(0.277)	(0.193)
Crime	0.766	0.492	0.678*	0.050	0.525*
	(0.557)	(0.366)	(0.399)	(0.453)	(0.302)
Physical activity					
Moderate activity	-0.030	-0.012	-0.068	0.038	-0.010
	(0.055)	(0.038)	(0.046)	(0.045)	(0.030)
Vigorous activity	0.183**	0.075	0.191***	0.027	0.112**
	(0.082)	(0.062)	(0.071)	(0.065)	(0.049)
Habits					
Smoke	0.737	1.070	1.170	0.054	0.723
	(0.749)	(0.834)	(0.771)	(0.744)	(0.526)

Still smoke	-0.072	-0.325	-0.534	0.670	-0.023
	(0.715)	(0.750)	(0.673)	(0.784)	(0.508)
Fruits	-0.066	-0.074	-0.137	-0.158	-0.086
	(0.315)	(0.202)	(0.256)	(0.236)	(0.170)
Vegetables	-0.022	-0.400**	-0.271	-0.430*	-0.294*
	(0.277)	(0.190)	(0.221)	(0.226)	(0.156)
Soft drinks	-0.194	0.367*	0.007	0.391*	0.222
	(0.280)	(0.194)	(0.229)	(0.232)	(0.158)
Observations	1,254	2,585	2,081	1,758	3,839

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis, clustered at household and province levels. All estimations include province fixed effects. Marginal effects are reported.

Table B9: Child labour effect on short-term emotions

	Worried	Bored	Happy	Angry	Lonely	Tired
Child work - Wages	1.856***	2.133***	-1.472	2.005***	-0.194	1.642*
	(0.611)	(0.736)	(1.955)	(0.589)	(1.419)	(0.923)
Demographics						
Female	0.007	0.215***	0.034	0.235***	0.116**	0.165***
	(0.050)	(0.052)	(0.051)	(0.046)	(0.048)	(0.058)
Age	0.020	-0.012	-0.007	-0.026*	-0.012	0.001
	(0.014)	(0.016)	(0.016)	(0.014)	(0.015)	(0.018)
Urban	0.020	0.098**	0.041	0.038	-0.022	0.050
	(0.047)	(0.048)	(0.050)	(0.044)	(0.045)	(0.056)
Married	0.013	-0.372***	0.154	-0.110	-0.219**	-0.138
	(0.098)	(0.096)	(0.112)	(0.096)	(0.086)	(0.114)
Divorced	0.159	-0.104	-0.447	0.294	0.334	0.053
	(0.218)	(0.255)	(0.300)	(0.213)	(0.277)	(0.353)
Childhood adversity						
Child health	0.010	0.067	-0.188***	0.057	0.036	-0.017
	(0.041)	(0.044)	(0.044)	(0.040)	(0.040)	(0.049)
Bed ridden	-0.096	0.083	0.004	0.042	0.064	0.049
	(0.073)	(0.085)	(0.089)	(0.077)	(0.081)	(0.091)
Child hunger	0.229**	0.104	-0.135	0.056	0.221**	0.001
	(0.109)	(0.123)	(0.126)	(0.096)	(0.109)	(0.123)
Parent smoke	-0.026	0.019	0.078*	0.019	-0.020	0.027
	(0.043)	(0.044)	(0.045)	(0.040)	(0.041)	(0.051)
Parent alcohol	0.071	-0.085	-0.053	0.005	-0.021	0.166
	(0.113)	(0.114)	(0.110)	(0.115)	(0.098)	(0.118)
Parent mental problems	0.089	0.226	-0.298	0.465	0.250	0.175
	(0.418)	(0.379)	(0.339)	(0.427)	(0.395)	(0.369)
Parents unmarried	0.004	0.028	-0.011	-0.023	0.029	0.039
	(0.061)	(0.069)	(0.065)	(0.058)	(0.057)	(0.071)
Religiosity						
Religious	-0.016	-0.123***	0.181***	-0.083**	-0.108***	-0.106**
	(0.043)	(0.045)	(0.044)	(0.039)	(0.042)	(0.049)
Willing to help	-0.476**	-0.335	0.291	-0.553**	-0.365*	-0.297
	(0.229)	(0.234)	(0.198)	(0.217)	(0.215)	(0.201)
Community participation	0.002**	-0.001*	0.001	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Physical health						
Chronic conditions	0.063**	0.112***	-0.034	0.097***	0.021	0.127***
	(0.032)	(0.032)	(0.036)	(0.030)	(0.032)	(0.036)
Acute morbidity	0.074***	0.035***	-0.001	0.048***	0.049***	0.068***
	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.011)
Health status	-0.230***	-0.231***	0.334***	-0.137**	-0.197***	-0.308***
	(0.062)	(0.064)	(0.066)	(0.059)	(0.062)	(0.069)
Days missed	0.013*	0.020***	-0.002	0.016**	0.014*	0.004
	(0.007)	(0.008)	(0.008)	(0.006)	(0.007)	(0.009)
Work status						
Employed	0.049	-0.260	0.777	0.725*	-0.086	0.246
	(0.224)	(0.261)	(0.514)	(0.415)	(0.276)	(0.324)
Unemployed	0.086	-0.101	0.824	0.731	-0.064	-0.299
	(0.234)	(0.273)	(0.541)	(0.450)	(0.278)	(0.290)
Schooling	0.092	-0.270	0.865*	0.632*	-0.211	0.123
	(0.220)	(0.287)	(0.451)	(0.337)	(0.289)	(0.311)
House keeping	0.040	-0.095	0.702	0.834*	-0.101	-0.241
	(0.256)	(0.297)	(0.545)	(0.499)	(0.288)	(0.315)
Education						
Education elementary	0.267	-0.016	0.070	-0.072	0.499	-0.183
	(0.265)	(0.269)	(0.322)	(0.246)	(0.322)	(0.354)

Education junior	0.540**	0.139	0.065	0.070	0.312	-0.075
	(0.254)	(0.251)	(0.304)	(0.240)	(0.263)	(0.352)
Education senior	0.501**	0.267	0.065	0.154	0.315	0.066
	(0.207)	(0.231)	(0.297)	(0.226)	(0.231)	(0.353)
Education tertiary	0.665**	0.439	0.038	0.204	0.464	0.077
	(0.286)	(0.283)	(0.306)	(0.256)	(0.296)	(0.369)
Body mass index						
Underweight	-0.042	-0.017	-0.035	0.003	-0.080*	0.024
	(0.044)	(0.045)	(0.045)	(0.040)	(0.042)	(0.051)
Overweight	0.073	0.057	0.023	-0.013	0.105	-0.076
	(0.070)	(0.072)	(0.076)	(0.063)	(0.073)	(0.080)
Obese	-0.026	0.072	0.003	0.063	-0.104*	0.032
	(0.064)	(0.070)	(0.065)	(0.063)	(0.059)	(0.076)
Current income proxies						
lnpce	0.045	0.080**	0.009	-0.018	0.043	0.125***
	(0.033)	(0.034)	(0.035)	(0.031)	(0.033)	(0.038)
Toilet river/land/sea	0.030	-0.102	-0.007	0.178**	0.012	-0.034
	(0.088)	(0.082)	(0.089)	(0.088)	(0.078)	(0.103)
Cook firewood	-0.037	0.025	0.003	-0.024	-0.030	-0.036
	(0.060)	(0.062)	(0.063)	(0.055)	(0.058)	(0.069)
Dependency ratio	-0.018	0.031	0.032	0.068	-0.027	0.080
	(0.056)	(0.057)	(0.060)	(0.052)	(0.054)	(0.065)
Past income proxies						
lnpce 2007	-0.018	0.030	0.003	0.052	0.049	-0.004
	(0.042)	(0.042)	(0.041)	(0.037)	(0.039)	(0.046)
Toilet river/land/sea 2007	-0.024	-0.043	-0.031	-0.069	0.028	-0.065
	(0.059)	(0.061)	(0.064)	(0.054)	(0.055)	(0.070)
Cook firewood 2007	0.058	0.043	-0.106**	0.030	0.096**	-0.005
	(0.051)	(0.052)	(0.053)	(0.047)	(0.048)	(0.057)
Dependency ratio 2007	-0.016	0.038	-0.107***	0.038	0.030	-0.044
	(0.032)	(0.035)	(0.035)	(0.033)	(0.031)	(0.038)
Stressful events						
Accident injury	-0.003	0.108	-0.117*	0.025	0.202***	0.190**
	(0.067)	(0.074)	(0.071)	(0.062)	(0.067)	(0.074)
Fall injury	0.087	0.118	0.027	0.144**	0.034	0.193**
	(0.074)	(0.081)	(0.077)	(0.071)	(0.071)	(0.081)
Natural disasters	-0.040	0.041	-0.155***	0.091*	0.042	0.033
	(0.048)	(0.053)	(0.052)	(0.049)	(0.050)	(0.057)
Injuries	-0.075	-0.066	0.064	0.095	0.078	0.104
	(0.126)	(0.149)	(0.140)	(0.133)	(0.121)	(0.145)
Disruption	0.032	0.069	-0.023	-0.029	0.029	0.038
	(0.049)	(0.052)	(0.054)	(0.044)	(0.050)	(0.059)
Crime	0.036	0.095	0.039	-0.027	-0.071	0.216**
	(0.080)	(0.087)	(0.083)	(0.073)	(0.075)	(0.095)
Physical activity						
Moderate activity	0.005	0.006	0.004	0.004	-0.006	0.016*
	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.009)
Vigorous activity	0.031**	0.019	-0.009	0.026**	0.017	0.063***
	(0.013)	(0.014)	(0.014)	(0.012)	(0.013)	(0.014)
Habits						
Smoke	0.064	-0.005	0.028	0.041	0.037	-0.212
	(0.145)	(0.165)	(0.159)	(0.135)	(0.174)	(0.166)
Still smoke	-0.134	0.096	-0.034	0.132	0.072	0.219
	(0.138)	(0.174)	(0.161)	(0.143)	(0.181)	(0.186)
Fruits	0.104**	-0.015	0.094**	0.059	0.069	0.105**
	(0.046)	(0.047)	(0.046)	(0.044)	(0.044)	(0.052)

Vegetables	0.072*	0.007	0.042	-0.049	-0.032	-0.047
	(0.040)	(0.044)	(0.043)	(0.039)	(0.040)	(0.048)
Soft drinks	0.110**	0.079*	0.029	0.128***	0.041	0.093*
	(0.043)	(0.045)	(0.045)	(0.039)	(0.042)	(0.049)
Observations	3,839	3,839	3,839	3,839	3,839	3,839

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis, clustered at household and province levels. All estimations include province fixed effects. Marginal effects are reported.

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Chapter 4

Can Unconditional In-kind Transfers Keep Children Out of Work and in School? Evidence from Indonesia

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ii. permission is granted for the candidate in include the publication in the thesis; and

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Abstract

The International Labour Organisation estimates that one in ten children are in child labour globally. Many of these children are also completely deprived of education, which creates a need for evidence-based interventions such as cash and in-kind transfers. However, there is limited evidence about the effect of in-kind transfers on child labour, impeding policy development. We address this gap by examining the impacts of an unconditional in-kind transfer, a nation-wide subsidised rice program, on child labour and schooling using longitudinal household survey data from Indonesia. To identify the causal effect, we employ coarsened exact matching with difference-in-differences estimator. The results indicate that the program is effective in decreasing the probability of working for boys though it does not have a significant impact on the probability of schooling. However, as an unconditional in-kind transfer, its ability to decrease child work for boys, especially of those who are both working and attending school, provides an important policy implication on how a food subsidy program can indirectly influence child wellbeing.

Keywords: Child labour; schooling; food subsidy; coarsened exact matching; Raskin; Indonesia

JEL classification: I21, I38, J82

4.1 Introduction

The International Labour Organisation estimates that 152 million children are in child labour globally, accounting for almost one in every ten children worldwide. Nearly half of these children (73 million) are engaged in hazardous work leading to adverse consequences on their wellbeing. Child labour also constitutes the violation of children's right to education, as 32 per cent of those in child labour are out of school and are completely deprived of education (ILO, 2017). These figures reveal that eliminating child labour remains formidable, and thus calls for evidence on the impact of policy interventions relevant to child labour and schooling (ILO, 2017). As household vulnerabilities connected with poverty are considered to be the root cause of child labour (Basu & Van, 1998; Edmonds, 2007; Jafarey & Lahiri, 2005; ILO, 2013; ILO, 2017), social protection programs are deemed as a potential mechanism in addressing it (ILO, 2017). There are various social protection tools that ensure income security and welfare of poor households. From a child labour perspective, instruments such as cash and in-kind transfers, social health protection and public employment programs are stated to be most relevant (ILO, 2013), even though the explicit objective of implementing those is not to reduce child labour.

This paper examines the impact of an 'unconditional' in-kind transfer, a food subsidy, on the labour supply and schooling of children. To this end, we consider one of the largest subsidised food programs known as 'Raskin' (or rice for the poor) that is currently in operation in Indonesia. By relying on a rich data source - Indonesia Family Life Survey (IFLS), we seek to answer two specific questions: (1) Does the food subsidy program provide a sufficient incentive for households to reduce the supply of child labour? (2) Does it induce an increase in schooling of children?

This study contributes to the growing literature on policy interventions in improving the welfare of children. First, it adds to the evidence on the effectiveness of social protection instruments on child labour and schooling, with reference to a subsidised food program in a less developed country. There is a plethora of studies that have examined the impact of cash transfers - both conditional and unconditional[1]- on child labour and schooling

[1] Both conditional and unconditional cash transfers provide households with an income transfer to address issues and vulnerabilities associated with poverty. However, in contrast to unconditional cash

in various country contexts.[2] Nevertheless, there is little empirical evidence on the child labour effects of other social protection tools, impeding policy development (de Hoop & Rosati, 2013; Edmonds, 2007; ILO, 2013; ILO, 2017). Particularly, when considering in-kind transfers, a small number of studies have only looked at the impact of 'conditional' in-kind transfers such as food for education programs and school vouchers on child labour and schooling. However, the limited evidence on such interventions is also inconclusive (ILO, 2013). According to the theoretical literature, unconditional in-kind transfers could be a potential source for eradicating child labour due to two reasons: (1) food-based social assistance programs have a significant influence on households by easing their budget constraints (Adelman et al., 2008; Alderman et al., 2018; ILO, 2013), (2) food and nutrition programs lead to considerable labour supply effects in both developed and developing countries (Currie & Gahvari, 2008). Therefore, to the best of our knowledge, this is the first study that seeks to examine the effect of an unconditional food subsidy on the labour supply and schooling of children.

Second, though the Raskin program was introduced in 1998, the impact on child labour does not appear to have been studied. (Gupta & Huang, 2018; US Department of Labour's Bureau of International Labour Affairs, 2015). Raskin was initially implemented as an emergency food security program. However, at present, it has become the largest social protection program in Indonesia. Given the magnitude of the program, it is interesting to examine to what extent such a well-established program could address vulnerabilities associated with poverty. To the best of our knowledge, this is the first evaluation of the Raskin program at the microeconomic level, which particularly looks at child wellbeing with regard to child labour and schooling.

Our study also differs from the existing impact evaluation studies in terms of methodology. The main identification issue arises from selection bias due to non-random distribution of the subsidy and unobserved heterogeneity. To address this, we implement the relatively new method of coarsened exact matching (CEM) with the difference-in-differences (DD) estimator. Compared to other commonly-used matching techniques, CEM has several

transfers, conditional cash transfers are given on a certain condition that the individuals receiving the transfer should fulfil specific requirements. For instance, maintaining regular attendance in school or ensuring regular health checkups (de Hoop and Rosati, 2014a; ILO, 2013).

[2]See Section 2.1 for a review of the empirical literature on the relevance of social protection tools against child labour and school drop-out.

desirable properties (as discussed in Section 4.5). Furthermore, combining CEM with DD provides an unbiased estimator which is robust to inherent unobservables (Gertler et al., 2011).

The results reveal that the subsidised rice program in Indonesia is effective in decreasing the probability of working for boys though there is no impact on the outcomes of girls. Specifically, we find that the Raskin program significantly decreases the likelihood of working for boys who engage in both working and schooling, by approximately 0.9 percentage points.

The remainder of the chapter proceeds as follows. Section 4.2 reviews the literature on the effects of social protection on child labour and school drop-out. Section 4.3 provides a brief background on the estimates of child labour and Indonesia's Raskin program. Section 4.4 presents the theoretical framework. Section 4.5 describes the data source and the variables used in the study. Section 4.6 outlines the empirical strategy, while Sections 4.7, 4.8 and 4.9 present the main results, robustness checks and discussion of results, respectively. The concluding remarks and policy implications are given in Section 4.10.

4.2 Effects of Social Protection on Child Labour and School Drop-out

In this section, we review the empirical literature on the relevance of social protection tools against child labour and school drop-out. We look separately at evidence concerning cash transfers (both conditional and unconditional), conditional in-kind transfers and other social protection tools such as social health protection, income security in old age and public employment programs.[3]

[3] A recent study by Dammert et al. (2018) provides a review of how social protection and labour programs can address child labour.

4.2.1 Cash Transfers

There is considerable evidence on the impact of cash transfers, both conditional and unconditional, on child labour in various country contexts.[4] The majority of these studies show that cash transfers are effective in keeping children out of work while encouraging school attendance, though the magnitude of the impact differs from one study to another based on various aspects.

When considering conditional cash transfers (CCTs), Mexico's flagship CCT program known as Progressa is one of the widely evaluated programs. This scheme provides low-income households with a monthly cash transfer, conditional on all household members using the provided health care services and children attend school. The value of the transfer is equal to 20 percent of the monthly income of the recipient household (ILO, 2013). According to Skoufias and Parker (2001), the program has a considerable effect on increasing school attendance and reducing the incidence of child labour of both boys and girls. Furthermore, they show that the impact on older boys and girls (i.e. among 12 to 17 year-olds) is much greater than that of younger boys and girls. This is because Progressa substantially increases transition into secondary school, possibly leading to a reduction in child labour among older children (Schultz, 2004). However, drawing evidence from the same program, de Janvry et al. (2006) argue that in the presence of income shocks CCTs are merely a safety net for the schooling of the children from poor households with minimal effect on child work.

Gee (2010) evaluates the effect of Nicaragua's Red de Protección Social (RPS) program on child labour in two aspects –the incidence and duration of child labour.[5] The findings show that the CCTs are effective not only in terms of reducing the probability that a child might work but also in terms of reducing the overall time involved in work activities.

Sparrow (2007) examines the impact of an Indonesian scholarship program (known as Jaringan Pengaman) on school enrolment, attendance and the supply of child labour. The findings indicate that the program has a significant effect on decreasing child labour as well as increasing school enrolment and attendance. In a subsequent study, De Silva

[4]see de Hoop and Rosati (2014a) for a systematic review on the effect of cash transfers on child labour
[5]This study focuses only on child labour outcomes.

and Sumarto (2015) examine the effectiveness of educational transfers targeted at poor students at all education levels introduced in 2008. Consistent with the findings of Sparrow (2007), this study also reveals that cash transfers conditioned on educational aspects provide the required incentive to forgo labour income, decreasing child labour supply. In a recent study in Nepal, Datt and Uhe (2018) emphasise that to achieve greater impacts on child labour, the income transfers should be of sufficiently sizeable value. According to this study, high-value scholarship-based transfers significantly reduce the total number of hours worked by girls aged 8 to 16 years, whereas low-value scholarships have no impact at all.

Contrary to above studies, Levy and Ohls (2007) show that the CCT program in Jamaica (known as Program of Advancement Through Health and Education (PATH)) does not significantly reduce child labour, though it increases school attendance by three per cent.[6]

In the context of unconditional cash transfers (UCTs), Edmonds and Schady (2012) provide evidence on Ecuador's unconditional cash transfer program - Bono de Desarrollo Humano (BDH). They show that the program reduces the likelihood of participating in both paid and unpaid activities among the children aged 11 to 16 years by eight per cent. Based on an unconditional cash transfer program implemented in Malawi, Covarrubias et al. (2012) also assert that providing cash transfers ensures not only the welfare of households but also has implications for economic development. However, in contrast to Edmonds and Schady (2012), the transfer scheme results in a reallocation of child's labour supply to family-based work such as household farm activities from work outside the household, rather than an overall reduction of work hours. This is presumably because of new productive investments (such as land, livestock or micro-enterprises) created by utilising the cash transfers. As such, the program has a limited impact on school enrolment.

The existing empirical evidence suggests that changes in child labour do not exactly correspond with a change in school participation (de Hoop and Rosati, 2014b). This means CCTs resulting in a substantial reduction in child work does not necessarily lead to a significant increase in school attendance or vice versa. Furthermore, it is also apparent

[6]This study examines the impact on school attendance instead of enrolment, as the enrolment rate in Jamaica is over 90 per cent.

that certain programs only have an impact on either child labour or schooling, but not both (e.g. PATH in Jamaica).

4.2.2 Conditional In-kind Transfers

In-kind transfers provide households with vouchers or food (usually dry rations) rather than cash. Similar to CCTs, conditional in-kind transfers are conditioned on specific behavioural requirements. In the context of child labour and education, food for education (FFE) programs and school vouchers are considered to be the most relevant types of conditional in-kind transfers.

Angrist et al. (2002) evaluate the effect of Colombia's Programa de Ampliación de Cobertura de la Educación Secundaria (PACES) – a school voucher program. Conditional on school attendance, this program provides low-income children with vouchers, which is sufficient to cover almost half of the cost of schooling. According to the authors, the program has a significant effect on improving educational attainment, though the impact on child labour is less prominent. Particularly, the program is not successful in reducing the percentage of children in work – both boys and girls. Nevertheless, it is effective in significantly reducing the number of hours worked by girls.

Considering food as an in-kind transfer, Kazianga et al. (2009) show that providing take-home rations can lead to a strong reduction in child labour activities among girls in Burkina Faso. Moreover, this study shows that providing school meals does not have an effect on the number of girls and boys engaged in any type of work activities. A similar study in Bangladesh finds that take-home rations reduce child labour in both labour market activities as well as household chores (Ravallion and Wodon, 2000). However, when compared to the magnitude of the increase in education, the reduction is low. Drawing evidence from a food for education program in Burkina Faso, de Hoop and Rosati (2014b) also assert that such programs are effective in increasing school attendance but have a limited impact in lowering child work.

In addition to the above studies, Cheung and Berlin (2015) and Meng and Ryan (2010) identify the impact of food for education (FFE) programs only on schooling outcomes in Cambodia and Bangladesh, respectively. Cheung and Berlin (2015) show that based on the program design, school enrolment increased by around 5 to 14 per cent. On the other hand, the FFE program in Bangladesh increased school participation rates by 15 to 26 per cent (Meng & Ryan, 2010). Furthermore, conditional on school participation, the eligible children are also likely to remain longer in school than their counterfactuals.

4.2.3 Other Social Protection Tools

Few studies have examined the effects of other social protection tools on child labour, particularly instruments such as social health protection and pension schemes. A study in Guatemala (Guarcello, Mealli & Rosati, 2010) examines the impact of health insurance on child labour. This study finds that the children in households where a household member has health insurance have lower participation in the labour market. According to the authors, health insurance can address the vulnerabilities caused by health shocks which is prominent in Guatemalan households and, thereby, decrease the necessity for additional income by means of child work. Similarly, in a recent study in Ghana, Garcia-Mandico et al. (2019) find that health insurance is effective in increasing both class attendance and school enrolment while reducing the incidence of child labour by eight percentage points. A similar finding is also reported by Strobl (2017), which shows that health insurance has additional benefits in lowering child labour and increasing schooling of children in Rwanda.

Thirumurthy et al. (2008) present evidence on the relevance of a particular health service on child labour in Western Kenya. Specifically, this study examines the impact of providing antiretroviral (ARV) treatment to HIV-positive adult household members on child work. The findings show that due to HIV treatment, there is a substantial and significant increase in the labour supply of HIV-positive adults, leading to spillover benefits within the household. The likelihood of working by young boys who live in a household where at least two members received ARV treatment declines by approximately 80 per cent, while there is no impact on the labour supply of young girls. Given the considerable effect on child labour supply, these results indicate the importance of providing required health protection so as to decrease the dependence on income from child work for basic survival.

In contrast to the above studies, Edmonds (2006) examines the impact of an old-age pension program on child labour in South Africa. The findings show that the pension benefits significantly reduce the overall time involved in labour activities, though it does not affect participation in child labour. In particular, boys experience a decrease in the number of hours engaged in market work, whereas girls experience a considerable reduction in the time engaged in domestic chores. The study also finds that school attendance among older children (13 to 17 years) increases significantly when an elderly person in the household starts receiving the pension. A similar study (de Carvalho Filho, 2012) demonstrates that Brazil's public pension program has no impact on the incidence and duration of child work activities of boys. Nevertheless, the program increases school enrolment for girls while reducing their labour participation, suggesting that pension schemes could improve child wellbeing.

The above review of the literature confirms two key points: (1) social protection tools are in fact relevant in mitigating the economic vulnerabilities related to child labour and school drop-out, (2) to date, no study has looked at the child labour and schooling impacts of unconditional in-kind transfers such as food subsidies. Therefore, this study seeks to fulfil this empirical gap by examining the effectiveness of a food subsidy program on reducing child labour and increasing schooling, considering Indonesia as a case study.

4.3 Background

4.3.1 Global Estimates of Child Labour and Education

The term child labour refers to work that has negative consequences on the wellbeing of children in terms of physical, social, psychological or educational development (Dayıoğlu, 2013; Edmonds, 2015) and thus, leading to a deprivation of their fundamental rights. There are two international conventions namely; International Labour Organisation (ILO) Minimum Age Convention No 138 and ILO Worst Forms of Child Labour Convention No. 182 that form the basis of defining the concept of child labour. Based on these two conventions, ILO defines 'child labour' as "all children under 15 years of age who are economically active excluding (i) those who are under five years old and (ii) those between 12 to 14 years old and spend less than 14 hours a week on their jobs, unless their activities or occupations are hazardous by nature or circumstance. Added to this are 15 to 17 years old children in the worst forms of child labour" (ILO, 2002, p. 32).[7] However, despite this standard definition, different countries tend to define child labour in various forms. This is because the extent to which 'child labour' differs from 'light work' depends on factors such as age, type of work, duration of work as well as rules and regulations implemented by individual countries (IPEC, 2004).[8]

According to the International Labour Organisation, there is a total of 152 million children aged 5 to 17 years in child labour worldwide. Child labour is predominantly seen in the regions of Africa, Asia and Pacific which together host nine out of every ten children in child labour (ILO, 2017). Since most of the African and Asian countries are agriculture-oriented, it accounts for 71 per cent of total child workers whereas the industrial and services sectors account for 12 and 17 per cent respectively.

Considering age profile, 48 per cent of child workers are in the age category of 5 to 11 years whereas 28 per cent are aged 12 to 14 years. Further, the boys are at a higher risk of child labour and the gender gap increases with age. As reported by the ILO (2017), the percentage of male child workers accounts for 58 per cent meaning there are 24 million more boys than girls in child labour. However, it is believed that such a noticeable gender gap may be as a result of underreporting of work activities by girls. This is because much of the household chores performed by girls as a form of work are not explicitly considered in estimating child labour.

One of the related issues of child labour is that it inevitably hinders the education of children in terms of low enrolment as well as performance. According to the International Labour Organisation (2017), 32 per cent of those children between 5 to 14 years who are in child labour are completely deprived of education. Though the remaining majority of children attend school while working, empirical studies have shown that these children

[7] Worst forms of child labour include both hazardous work and unconditional worst forms of labour. Hazardous work is defined either as "(i) work which exposes children to physical, psychological or sexual abuse; (ii) work underground, underwater, at dangerous heights or in confined spaces; (iii) work with dangerous machinery, equipment and tools, or which involves the manual handling or transport of heavy loads, (iv) work in an unhealthy environments; or (v) work under particularly difficult conditions such as work for long hours or during the night. Unconditional work forms of labour include all forms of slavery, child prostitution and trafficking of children" (ILO, 2002, p.34).

[8] The term 'light work' is not deemed 'child labour'. According to ILO (2002), "light work should (i) not be harmful to a child's health and development and (ii) not prejudice attendance at school and participation in vocational training" (ILO, 2002, p.32)

also perform poorly in school leading to low educational attainment (Edmonds, 2007; Emerson et al., 2017). Thus, to address the serious issue of child labour and low schooling, as evident by the above statistics, the Sustainable Development Goals include a renewed global commitment to end child labour by 2025 (ILO, 2017).

4.3.2 Child Labour and Education in Indonesia

As a developing country, Indonesia has a high incidence of child labour leading to low educational attainment. Education is compulsory for Indonesian children aged seven to fifteen years. As a result, the country has made significant progress in ensuring more than 95 per cent of children aged between 7 to 12 years are attending primary or junior secondary school. Despite high enrolment rates, many children do not complete all levels of formal education; 1 in 10 children do not transit from primary to junior secondary level, and almost 1 in 5 children who complete junior secondary do not continue into the final years of their education (UNICEF, 2016).[9] Low transitions from primary to secondary school is mainly seen among children from low-income families and rural areas. According to BAPPENAS and UNICEF (2017), on average, 3.5 million children were out of secondary school in 2015. One of the main reasons for high drop-out rates is poverty, forcing the children to engage in some form of child labour while depriving them of their right to education.

Child labour is a widely observed practice in Indonesia (BPS & ILO, 2010). Across Indonesia, 6.9 per cent of children were in child labour in 2009 (BAPPENAS & UNICEF, 2017). Alarmingly, close to half of these child workers are engaged in hazardous work (BAPPENAS & UNICEF, 2017). Child labour is mainly seen in rural areas with 12.5 per cent of children aged 10 to 17 years working, compared to that of 5.9 per cent in urban areas (as cited in US Department of Labour's Bureau of International Labour Affairs, 2015). In line with the global trends of child labour, the highest number of children aged between 10 to 14 years are employed in the agricultural sector which accounts for 62 per

[9] As cited in UNICEF Indonesia (10 November 2018) Retrieved from https://www.unicef.org/indonesia/education.html

cent, whereas the industrial and services sector consists of 12 per cent and 26 per cent respectively.

Though most of the working children attend school, it certainly limits the time available for education hindering their ability to reach the potential. Based on the 2015 Programme for International Student Assessment (PISA), less than half of the students aged 15 years achieve a minimum proficiency in reading and mathematics (BAPPENAS & UNICEF, 2017). Therefore, as a developing country, eliminating child labour while increasing educational attainment is crucial for the country's sustainable economic growth and development.

4.3.3 The Raskin Program

In order to address the problem of poverty as well as issues arising out of it, several social protection programs are implemented by the government of Indonesia. 'Raskin' (or rice for the poor) is one of the cross-sectoral national programs intended to alleviate poverty and provide social protection which is funded by the central government. Raskin was first introduced in 1998 as an emergency food security program in the form of subsidised rice assistance prioritised to poor and vulnerable households.[10] However, at present, it has become a permanent nation-wide social protection program targeted at the poorest 40 per cent of the households in Indonesia with the largest government budget allocation (Banerjee et al., 2016; Trimmer et al., 2018; World Bank, 2012).

The targeted households are selected using a proxy-means test. In addition to the income of the household, factors such as the number of toddlers and school-age children in the household, whether the household head is a female and the physical condition of the house are also considered in determining the eligibility for the program.[11] However, there is no specific selection criterion for the program as it has changed several times based on the data sources used (Trimmer et al., 2018). In general, there is little control by the central

[10] Initially, this program was named as Operasi Pasar Khusus (OPK) meaning Special Market Operation. The government changed its name to 'Raskin' (rice for poor families) in 2002. In 2016, it was again renamed as Rastra (literally prosperous rice).

[11] As cited in Rastra - Rice for Family Welfare (25 July 2018) Retrieved from http://raskin.bangda.kemendagri.go.id /tentang-raskin/tujuan-raskin.html.

government in monitoring and determining the eligibility, since the local officials have substantial authority over the implementation of the program at the local level (Banerjee et al., 2016; World Bank, 2012). As a result, Raskin has been criticised for considerable 'leakages' where eligible households obtain less than 35 per cent of the intended subsidy (see Banerjee et al., 2016; Trimmer et al., 2018).

The rationale of the program is to reduce the burden of household expenditure on food. In poor households, the food expenditure constitutes the largest share of its total expenditure which can range from 45 to 77 per cent (Banerjee & Duflo, 2011). As rice is considered to be the staple food in Indonesia, an increase in the price of rice can adversely affect the purchasing power of the poor. This is because rice accounts for almost a quarter of the average monthly expenditure in poor households, contributing around 34 per cent and 26 per cent to the official rural and urban poverty budgets, respectively (Sumarto & Widyanti, 2008; Trimmer et al., 2018). Hence, by providing a certain quantity of rice at a subsidised price could lead to ease the budget constraints of poor households vulnerable to child labour (ILO, 2013).

This program allows the beneficiary households to purchase up to a maximum of 15 kilograms of medium quality rice per month at a subsidised rate of one-fifth of the market price (Banerjee et al., 2016). To put these numbers into perspective, the intended subsidy value of the allocation of 15 kilograms of rice accounts for about five per cent of the monthly consumption expenditure of those households who are below the poverty line. It is also shown that ensuring accurate targeting of the program could reduce poverty by about 1.2 per cent or 2.69 people (The State Ministry of National Development Planning - Indonesia, 2013).[12] Raskin also benefits the children of poor households. Specifically, almost half of the children live in a household that receives Raskin rice (BAPPENAS & UNICEF, 2017). As a food subsidy, Raskin improves the nutrition status of children. This, in turn, could lead to important implications on reducing child labour and increasing schooling.

[12] As cited in Rastra - Rice for Family Welfare (25 July 2018) Retrieved from http://raskin.bangda.kemendagri.go.id /tentang-raskin/tujuan-raskin.html.

4.4 Theoretical Framework

In this section we present a simple theoretical framework of child labour and schooling decision. According to Ersado (2005), this decision is determined by the maximisation of household's utility on consumption and leisure subject to both budgetary and time constraints of the household. Following Ravallion and Wodon (2000), our model is based on a representative household where parents decide on how to allocate the time of their children. Therefore the utility function of the parents is:

$$U = U(C, S, H : \mathbf{X}) \tag{1}$$

where U is a concave utility function with household's current consumption (C), child's school attendance (S), child's leisure time (H) and a vector of exogenous child, household and parent characteristics $\mathbf{X}$. We include child's schooling in the utility function on the assumption that schooling is both a consumption and an investment good for the parents (Becker & Lewis, 1973). The child-time constraint that maximises utility can be expressed as:

$$T = S + L + H \tag{2}$$

where the child's total time (T) is allocated between schooling (S), paid and unpaid labour supply (L) and leisure (H). The household's budget constraint is determined by the income (Y) which the household receives from other sources (this is assumed to be a function of $\mathbf{X}$), income from child labour as well as the financial benefit of the rice subsidy.

$$C = Y(\mathbf{X}) + wL + bR \tag{3}$$

where w is the wage rate for child labour, and b is the monetary value of the subsidised rice (R) received under the Raskin program.

Maximising (1) subject to (2) and (3), is equivalent to maximising (1) with respect to C, H and S, subject to:

$$C + wS + wH = Y(\mathbf{X}) + wT + bR \tag{4}$$

which shows that w is also the price of schooling. Deriving the first-order conditions of the model yield the following optimal outcome;

$$\frac{MU_C}{MU_S} = \frac{MU_C}{MU_H} = \frac{1}{w} \tag{5}$$

which suggests that at the optimum the parents' choice equates the marginal rate of substitution (MRS) between consumption and schooling with the MRS between consumption and leisure and both these equate the price of school and leisure w. Accordingly, an increase in the wage rate would lead to a reduction in both schooling and leisure while increasing the labour supply of children.

Since the receipt of the food subsidy does not depend on whether the child goes to school or works, it will not have any impact on the wage rate. Nevertheless, the monetary benefit derived from it would generate an income effect leading to an increase in household consumption and schooling, assuming that both are normal goods. However, whether the subsidy would have an effect on keeping the children out of the labour market depends on the cross-effect between schooling and leisure (Ravallion & Wodon, 2000). If schooling and leisure are strong substitutes, then an increase in schooling would not necessarily lead to a reduction in child labour. In other words, if the subsidised program is to be successful in achieving both an increase in schooling and a decrease in child labour, schooling and leisure should be complements. Our empirical analysis aims to shed some light with regard to these effects.

4.5 Data

4.5.1 Data Source, Sample and Variable Definitions

The data source that we use for the empirical analysis is the Indonesia Family Life Survey (IFLS). The IFLS is an ongoing longitudinal survey with unique features such as low attrition (see Section 1.3.2). Currently, there are five waves covering years 1993 (IFLS 1), 1997/98 (IFLS 2 and IFLS2+), 2000 (IFLS 3), 2007 (IFLS 4) and 2014 (IFLS 5). For this study, we use data from 1997, 2000, 2007 and 2014 waves of the IFLS.[13]

Our sample is restricted to children between the age of 5 to 14 years old, as child labour is defined as children aged 5 to 14 years who are economically active. The term 'economically active' refers to the participation in the production of economic goods and services, meaning it can be either for wages or as unpaid work performed as part of family business (Edmonds, 2007). Therefore, the supply of labour for household activities and chores are not considered as child labour.[14]

In our study, there are two main outcome variables of interest - child labour and schooling. The data in relation to these is extracted from the child module of the IFLS, which is administered to children below 15 years old.[15] Constructed as binary variables, child labour takes on a value of 1 if the child has ever worked and 0 otherwise.[16] Similarly, schooling takes on a value of 1 if the child is currently in school and 0 otherwise. The treatment variable used in this study is a dummy variable which is assigned a value of 1 if the household has ever bought subsidised rice from Raskin program during the past year and 0 otherwise.

[13] We do not use data from the first wave IFLS1 (1993) due to the differences in the format of the questions and the considerable number of missing observations on parental information.

[14] The data on child' s participation in household chores are provided only in 2007(IFLS 4) and 2014 (IFLS 5) waves.

[15] This means the respondent is usually a child below 15 years old. Sometimes the questions are answered by an older sibling or another household member such as mother, aunt or grandmother who deemed the most knowledgeable source of information for the child.

[16] From the year 2000 onwards, the child module contains separate questions on the child's work status for the last month, week and ever as well as type of work. However, to ensure consistency of the child labour measure across different waves, we have used the ever worked participation.

We control for an extensive set of socio-demographic covariates that are well established in the literature. Specifically, we include child's age, religion, parental characteristics such as parent's age, marital status, occupation and educational attainment as control variables. Furthermore, we also include variables on the household's demographics, such as household size, dependency ratio, the gender of the household head and ownership of assets. Standard indicators such as access to electricity, water, proper sanitation and source of fuel are included as housing characteristics. The monthly per capita expenditure, which is constructed by adding both food and non-food expenditure, is used to proxy for household income. Moreover, we also consider regional heterogeneity by including a dummy variable for urban area as well as provincial dummy variables in our estimation. A complete list of variables used in this study is presented in Table C1.

As the Raskin program began in 1998, there is one pre-exposure period: 1997 and three potential post-exposure periods of 2000, 2007 and 2014. However, since there is a seven-year gap between the subsequent waves after year 2000, the use of panel data leads to a loss of significant number of observations. This is because children who are eight years or older in 2000 are excluded from the child modules in 2007 and 2014 waves as they would be above 15 years of age. Therefore, we use pooled cross-section data to maximise the number of observations.[17] Accordingly, our sample consists of 23,531 children (Girls - 11,492 and Boys - 12,039) between the age of 5 to 14 years from 6,889 households. After excluding observations with missing responses, 23,028 observations are used in the estimation.[18] Approximately 66 per cent of the households have received Raskin at least once in a year.

4.5.2 Descriptive Statistics

Table C2 in Appendix presents the summary statistics. The sample is balanced in terms of gender, and the average age is 9.5 years. Half of the children are from a rural household. Around 20 per cent of the children are in poverty as reflected by the household

[17]The use of panel data from waves 2 (1997) and 3 (2000) results in a small sample size as the majority of the households with working children in wave 3 have missing data on the receipt of Raskin.

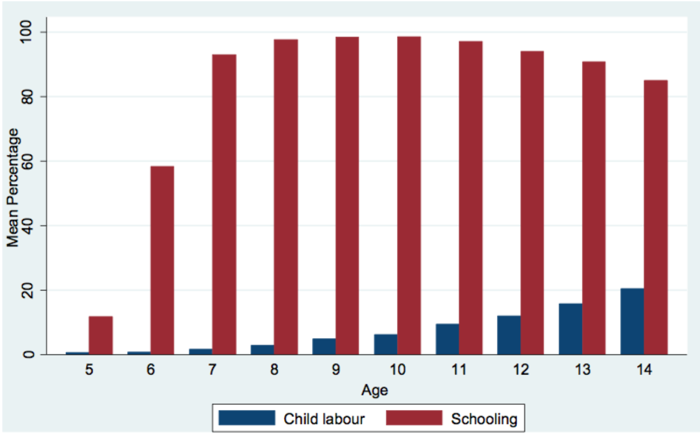
[18]Due to the significant number of missing observations on parents' characteristics, we include dummy variables indicating missing values to preserve sample size.

characteristics such as poor sanitation and use of nearby river, land or sea as the toilet. Approximately, eight per cent of children are engaged in work which corresponds to the actual percentage of child labour in Indonesia. On average, 83 per cent of children are currently attending school.

Figures 4.1 and 4.2 depict the distribution of child activity by age. According to Figure 4.1, the involvement in child work rises steadily with age. The percentage of children in school shows a sharp rise until the age of eight years and begins to decline after ten. This clearly depicts the trade-off between work and school as children tend to work more and attend school less as they get older. Figure 4.2 provides a detailed overview of child activity. In line with Figure 4.1, the percentage of children attending school and engaging in employment increases with age. A higher proportion of children aged 5 and 6 years are neither working nor attending school. This is expected as the minimum age for compulsory education in Indonesia is seven years. Interestingly, the proportion of inactive children reduces drastically until age nine and shows a gradual increase with age. Given that it is mandatory to attend school until the age of 15 years, the reasons for the increase are unclear, which is beyond the scope of this chapter.

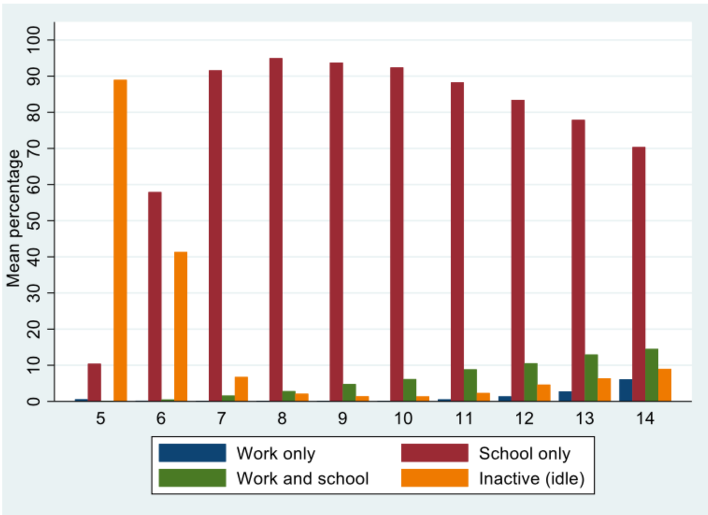
Figures 4.3 and 4.4 illustrate the child activity by gender and place of residence. In general, girls are more likely to attend school while boys engage solely in work activities. Notably, we find that the proportion of children who are inactive as well as perform both activities is higher among boys compared to that of girls. Considering the place of residence, children from a rural household tend to work more and thus be out of school. As shown in Figure 4.4, the involvement in all activities except attending school only, is higher among rural children than that of urban children.

Figure 4.1: Distribution of child work and school by age



Note: This figure is based on data from the 1997, 2000, 2007 and 2014 waves of the IFLS.

Figure 4.2: Distribution of child activity by age



Note: This figure is based on data from the 1997, 2000, 2007 and 2014 waves of the IFLS.

Figure 4.3: Child activity by gender

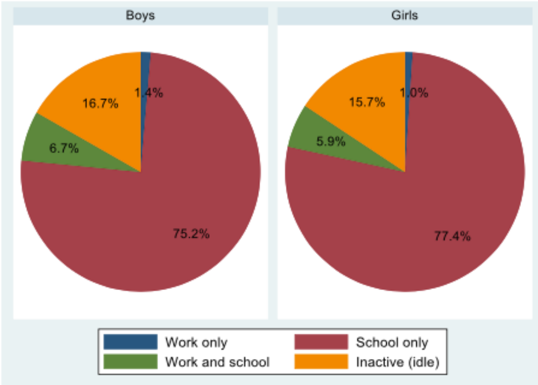
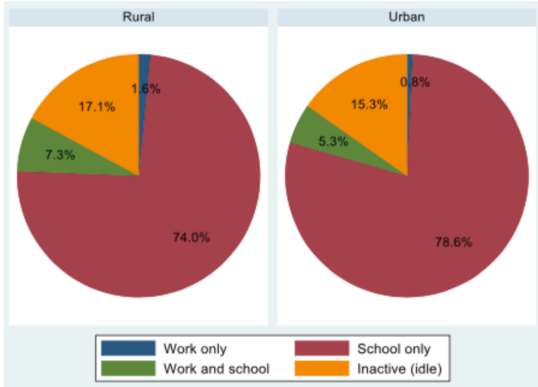


Figure 4.4: Child activity by residence



Note: The figures are based on data from the 1997, 2000, 2007 and 2014 waves of the IFLS.

To understand the context in terms of those who receive Raskin and those who do not, we derive the descriptive statistics by the control and treatment assignment. Table C2 in Appendix reports the mean values across groups and the results of t-tests on the difference of means. When considering the mean values of the outcomes variables of child labour and schooling, it is evident that there is a significant difference between the control and treatment groups. As anticipated, the households that receive Raskin have a higher proportion of children involved in child labour and a lower proportion of children in school. Furthermore, as expected, there are also significant differences across the control and treatment groups, especially in terms of household and parent characteristics. This is because as Raskin is targeted at the poorest households, the two groups are likely to differ in variables that capture the aspects of poverty. In general, the households that receive Raskin are poorer and less educated. Such significant differences in the two groups may imply that there is non-random selection into treatment, and thus the control group may not act as a perfect counterfactual to the treatment group.

4.6 Empirical Strategy

Our estimation strategy begins with establishing a causal relationship between receiving Raskin and the outcome variables of child labour and schooling. As formalised in Rubin (1974), the treatment effect for individual i is difference between the individual's potential outcome Y_{1i} with treatment (D_i= 1) and potential outcome Y_{0i} without treatment (D_i

= 0), that is:

$$TE_i = Y_{1i} - Y_{0i} \tag{6}$$

However, the main challenge in causal inference lies in measuring the treatment effect (TE_i). This is because in observational data an individual can only be in one of the two states of the world at a given time, which is known as the 'fundamental problem of inference' (Holland, 1986). Instead, what we can actually observe from the data are the outcomes of the individuals who have received the treatment and those who have not received it. Therefore, to overcome this problem we consider the measure of interest as the average of TE_i over the selected sample - the sample average treatment effect on the treated (Heckman et al., 1998) defined as:

$$SATT = \frac{1}{N}\sum_{i=1}^{N_T}[TE_i|D_i = 1] \tag{7}$$

where $N_T = \sum_{i=1}^{N} D_i$. SATT is the mean effect of actual program participants which can be decomposed as:

$$SATT = E\left(Y_1|D = 1\right) - E\left(Y_0|D = 1\right) \tag{8}$$

According to the above, the counterfactual mean of the treated, $E\left(Y_0|D = 1\right)$ is unobservable. As an alternative, the mean outcome of the untreated individuals $E\left(Y_0|D = 0\right)$ can be used, provided that there is random assignment. However, given that this study is based on non-experimental data, $E\left(Y_0|D = 0\right)$ would not be a good substitute as the variables that determine the program participation would also affect the decision of child labour and schooling. In other words, the households that are meant to receive Raskin are in fact the poor households with a high probability of child work and low schooling. This means that the treated and the control groups differ in terms of other covariates leading to selection bias (Caliendo & Kopeining, 2008; Heckamn et al., 1998).

Previous studies on program evaluation have relied on techniques such as randomised controlled trial (RCT), difference-in-differences (DD), regression discontinuity design

(RDD), matching or a combination of aforesaid methods to deal with sample selection bias arising from non-random assignment of the treatment and unobserved heterogeneity. In this study, we use a matching technique combined with difference-in-differences (matched DD) to estimate the treatment effect. We select matching as the identification strategy for two reasons. First, the Raskin program does not have any clear assignment rules such as an eligibility score (Trimmer et al., 2018) that explain why some households received the rice subsidy and others did not. Second, the availability of a rich data source that contains data on both households that received Raskin and that did not, enables us to estimate a control group that has as similar as possible characteristics as the treatment group (Gertler et al., 2011).

There are several types of matching methods that are widely applied in the empirical literature. These methods differ primarily on the technique that is used to find at least one control unit for each of the treated units that is similar on the covariates. However, the major limitation of using the common matching methods, such as propensity score and Mahalanobis matching, lies in the fact that they do not necessarily guarantee a reduction of imbalance (i.e. differences between the treated and control groups) in a given data set. For instance, the application of propensity score matching leads only to an improvement of balance on some covariates while decreasing the balance on other covariates (Iacus et al., 2012). Moreover, these methods depend on a set of unverifiable assumptions about the data generation process and despite such assumptions, its properties only hold on average across samples. Therefore, the use of these techniques can increase both model dependence and imbalance (Iacus et al. 2012); meaning that they are ad-hoc and inefficient (Blackwell et al. 2009). As a solution for these problems we employ coarsened exact matching (CEM) proposed by Iacus, King and Porro (2012) which is explained in detail below.

4.6.1 Coarsened Exact Matching

Following Iacus et al. (2012), the basic idea of CEM can be explained in three steps. First, it temporarily coarsens each covariate to reduce the differences between the treated and control groups in terms of observables. Second, it applies exact matching to the coarsened data and generates weights to each matched unit. Finally, the original values of the matched units along with the CEM weights are used to estimate the average treatment effect on the treated (ATT).

As an exact matching technique, CEM belongs to the class of monotonic imbalance bounding (IMB) matching methods. Therefore, in contrast to other matching methods, CEM balances between the control and treatment groups chosen ex-ante, and adjusting the imbalance on one covariate does not affect the balance of any other (Blackwell et al. 2009). Hence, it is shown that CEM can reduce imbalance, model dependence, estimation error, bias, variance and mean squared error. Additionally, CEM also possesses several beneficial properties. First, CEM meets the congruence principle meaning both the data space and the analysis space are similar. Second, CEM automatically restricts the matched data to areas of common empirical support. Finally, CEM is computationally very efficient, even for large datasets. Therefore, contrary to the previous empirical literature on child labour, we use CEM to deal explicitly with the treatment selection bias owing to its desirable features.

4.6.2 Matched Difference-in-Differences

The presence of data in relation to before and after intervention allows us to combine the coarsened exact matching with the difference-in-differences (DD) technique. Following Ravallion (2007), panel data are not necessary for calculating DD. This is because the double-difference estimator which provides the mean treatment effect on the treated for period one can be derived as follows:[19]

$$DD = E\left(Y_1^T - Y_0^C | T_1 = 1\right) - E\left(Y_1^C - Y_0^C | T_1 = 0\right) \tag{9}$$

It is apparent that what is required is the set of four means that make up DD; where the means need not be calculated for the same sample over time.

To employ the DD technique, we first restrict our sample to households that are observed in both pre and post-treatment periods. Since there is no specific rule followed in determining which households are eligible for the receipt of Raskin in the pre-treatment

[19] See Ravallion (2007) for detailed derivation.

period, we use post-treatment period data to identify the treated and control households in the pre-treatment period. By using pooled data over both time periods and across treatment status, we then estimate the following regression:

$$Y_{it} = \alpha + \gamma T_{i1} + \delta t + \beta T_{i1} t + \eta \mathbf{X}_{it}^{'} + \varepsilon_i \qquad (t = 0, 1;\ i = 1, ..., n) \tag{10}$$

where Y_{it} is the outcome measure for the ith individual observed at two time periods, t = 0,1; T_{i1} is the treatment status in period one, with $T_{i1} = 1$ if the individual receives the program (is 'treated') and $T_{i1} = 0$ otherwise; $\mathbf{X}_{it}$ is a vector of covariates. The regression coefficient β on the interaction effect between the treatment dummy variable (T_{i1}) and time (t) identifies the DD impact.

Combining coarsened exact matching with DD, allows us to offset any limitations of matching as an identification strategy and thereby to increase the robustness of the estimated counterfactual (Gertler et al., 2011). Since matching is simply a data-preprocessing technique, it is required to use a parametric model to estimate the causal effect. According to Ho et al. (2007), applying a matching method to the data before analysis reduces model dependence.

4.6.3 Empirical Model

We employ a bivariate probit model to estimate the effect of Raskin on the likelihood of child labour and schooling. Given that both outcomes are denoted as binary variables, a bivariate probit model allows us to model child labour and schooling jointly as both are interrelated decisions that compete for a child's time. In contrast to a univariate probit model, a bivariate probit model can capture any interrelation between work and schooling by identifying the correlation between the unobservables of the two outcome variables.

Incorporating equation (5), the bivariate DD model is derived as follows:

$$Work^*_{1it} = \alpha_1 + \gamma_1 Raskin_{1it} + \delta_1 Post_{1it} + \beta_1 Raskin * Post_{1it} + \eta_1 \mathbf{X}'_{1it} + \varphi_{1i} + u_{1it} \quad (11)$$

$$Schooling^*_{2it} = \alpha_2 + \gamma_2 Raskin_{2it} + \delta_2 Post_{21i} + \beta_2 Raskin * Post_{21i} + \eta_2 \mathbf{X}'_{2it} + \varphi_{2i} + u_{2it} \quad (12)$$

where the observed outcomes are:

$$Work_{1it} = \begin{cases} 1, & \text{if } Work^*_{1it} > 0 \\ 0, & otherwise \end{cases} \quad (13)$$

$$Schooling_{2it} = \begin{cases} 1, & \text{if } Schooling^*_{2it} > 0 \\ 0, & otherwise \end{cases} \quad (14)$$

where $Work_{1it}$ =1 if the child has ever worked in year t and 0 otherwise; $Schooling_{2it} = 1$ if the child is currently in school in year t and 0 if not.[20] $Raskin_{it}$ is a dummy variable that equals to 1 if the child i lives in a household that receives Raskin in year t and 0 otherwise. $Post_{it}$ is an indicator variable for the period after Raskin was introduced. This takes on a value of 1 for the years 2000, 2007 and 2014 and 0 for the year 1997. Our variable of interest is $Raskin * Post_{it}$ which equals to 1 if the child i lives in a household that receives Raskin in post period and 0 otherwise. Vectors $\mathbf{X}_{1it}$ and $\mathbf{X}_{2it}$ represent individual, parent and household covariates that affect child labour ($Work_{1it}$) and schooling decision ($Schooling_{2it}$), respectively. φ_i denotes the household fixed effects. The error terms u_{1it} and u_{2it} come from a bivariate normal distribution with $Cov\left[u_{1it}, u_{2it} | X_{1it}, X_{2it}\right] = \rho$

In the event where $\rho = 0$, the model collapses into two separate probit models for $Work_{1it}$ and $Schooling_{2it}$. If ρ is significant we can conclude that there is a correlation between the unobserved factors affecting both working and schooling. In such a case, the results of the univariate probit model would be inefficient and biased (Wooldridge, 2010).

[20] $Work^*_{1it}$ and $Schooling^*_{2it}$ represent the latent variables of desire to work and attend school respectively.

4.7 Empirical Results

4.7.1 Coarsened Exact Matching Results

We begin our empirical analysis with coarsened exact matching (CEM). The first step of CEM is to select the control variables to be included in matching. In view of Heckman et al. (1998), all variables that can affect both treatment assignment and outcome should be included in the matching process to satisfy the assumption of strong ignorability. In this study, we match the treated and the control households based on the observable household characteristics that act as proxies for household's poverty level and thus leads to treatment assignment. This is because, as a food subsidy Raskin is targeted at the poorest households, which is determined by the level of household's income and welfare. Therefore, based on a probit estimation, we identify the significant covariates that determine Raskin and hence mimic the rules of eligibility into the program (see Table C3 in Appendix). Accordingly, the covariates that are used for the coarsening process are, place of residence (urban or rural), household size, dependency ratio, per capita expenditure, ownership of business, access to electricity, whether the household purchases water, uses firewood for cooking, uses the nearby river, land or sea as the toilet and poor sanitation.[21]

The quality of the matching outcomes on pre-treatment data (i.e. wave 2) is diagnosed by an assessment of covariate balance. Table C5 in Appendix reports the results for both pre- and post-matching of the sample. According to Table C5, the overall multivariate imbalance decreases from 0.91 to 0.68. There is also a significant reduction in the univariate imbalance for each of the covariates. Further, the post-match mean differences between treated and control groups are almost negligible. This suggests that CEM has produced a reasonable match.

It is important to note that with coarsening, there would be some imbalance remaining in the matched data. According to Blackwell et al. (2009), such imbalance can be controlled

[21] As CEM is an exact matching technique, it is important to limit the number of covariates used in the coarsening process to avoid the curse of dimensionality. Therefore we select only those variables that are significant at 1% level. Since assets per capita and per capita expenditure are continuous variables, the inclusion of both leads to poor matching outcomes. Hence, out of these two, we select per capita expenditure for matching based on the magnitude of the effect. The use of assets per capita instead of per capita expenditure provide qualitatively similar results (see Section 4.7.2).

via a statistical model. Therefore, we use a bivariate probit model with a double-difference approach on the matched data to estimate the causal effect of Raskin on child labour and schooling. The weights generated by the CEM process are also included in the model, to equalise the number of treated and control units within each stratum (Iacus et al., forthcoming).

4.7.2 Bivariate Probit Estimates

Panel A of Table 4.1 reports the main regression results of the bivariate probit model.[22] As a benchmark, we also report the estimates without the corresponding matching weights (Columns 1 and 2). The correlation coefficient between the error terms - rho (ρ) is significantly different from zero for both estimations at 1% level. This confirms the importance of employing the bivariate probit model as the estimations derived from a univariate model would be inefficient. As expected, its sign suggests that there is a negative correlation between the unobserved factors affecting the probability of working and attending school. In Table 4.1, the estimated coefficient of Raskin*Post is the treatment effect of receiving Raskin on the probability of working as a child or attending school. The DD specification without matching weights suggests that Raskin decreases the probability of child work while increasing the probability of schooling for children. However, these estimates could be biased due to possible selection bias. Thus, our preferred estimation is a bivariate probit model with matched DD. Column 3 shows that, on average, Raskin decreases the likelihood of child labour which is significant at 5% level. The estimated coefficient on schooling is positive though it is not statistically significant from zero.

[22] The reported results are with robust standard errors clustered at both household and province levels. Clustering at municipalities and subdistricts levels also provide quantitatively similar results.

Table 4.1: Effect of Raskin on child labour and schooling

Panel A - Bivariate Probit Estimates

	DD without CEM weights		DD with CEM weights	
	(1)	(2)	(3)	(4)
	Work	School	Work	School
Post	1.089***	-0.640***	1.096***	-1.145***
	(0.128)	(0.083)	(0.309)	(0.227)
Raskin	0.250**	-0.142**	0.403**	-0.096
	(0.108)	(0.063)	(0.196)	(0.117)
Raskin*Post	-0.250**	0.217***	-0.505**	0.206
	(0.115)	(0.068)	(0.232)	(0.152)
Rho	-0.269***		-0.254***	
	(0.026)		(0.066)	

Panel B - Average Marginal Effects

	Work only (work=1 school=0)	School only (work=0 school=1)	Both (work=1 school=1)	Idle (work=0 school=0)
Post	0.025***	-0.204***	0.058***	0.121***
	(0.009)	(0.034)	(0.018)	(0.025)
Raskin	0.005**	-0.040**	0.028**	0.008
	(0.002)	(0.020)	(0.013)	(0.013)
Raskin*Post	-0.007**	0.062**	-0.036**	-0.019
	(0.003)	(0.026)	(0.018)	(0.017)
Observations	4,309	4,309	4,309	4,309

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include the full set of control variables as given in Appendix Table C1, household, year and province fixed effects as well as the corresponding weights generated by CEM. See Tables C6 and C7.1 in Appendix for comprehensive results.

Panel B of Table 4.1 presents the average marginal effects of the estimated coefficients from the matched DD model. Given that we use a bivariate probit model, there are four observed joint outcomes of work and school. Specifically, with regard to treatment effect, it is possible to identify the impact of receiving Raskin on the probability of: (1) working only, (2) schooling only, (3) both working and schooling (4) neither working nor schooling (idle). We find that receiving Raskin decreases the probability of engaging solely in child labour by 0.7 percentage points. Moreover, it increases the probability of only attending school by 6.2 percentage points. Interestingly, Raskin decreases the probability of working and attending school simultaneously by 3.6 percentage points. This implies that the decrease in child labour occurs among those children who are both working and schooling, resulting in a corresponding increase in the likelihood of schooling only.[23]

Consistent with existing empirical studies, Table C7 in Appendix reveals that variables such as gender and age of the child, wealth and assets of the household and parental education level are all significant determinants of child labour and schooling with the expected signs. Being a girl reduces the probability of working while increasing the probability of schooling. This is expected because compared to girls, boys generally have higher participation in market work meaning lower likelihood of just attending school, which is also observed in the context of Indonesia (De Silva & Sumarto, 2015; Suryahadi et al., 2005). We further find that an increase in age is associated with an increase in the probability of both working and schooling while reducing the proportion of inactive children. Notably, parental education, especially that of mother's, have a significant impact on the working and schooling decisions of children. An increase in the level of maternal education decreases the probability of work by approximately 0.6 to 0.7 percentage points while increasing the likelihood of schooling by seven to ten percentage points.

As a goodness-of-fit measure, we report the comparison of the sample means of actual work-school outcomes versus the predicted probabilities after bivariate probit model. Table C8 in Appendix shows that the estimated model performs well such that the predicted probabilities are almost similar to that of actual sample means.

4.7.3 Gender Heterogeneity

As shown in Section 4.6.2, gender differences play a significant role in determining participation in child work and schooling. Therefore, we perform a heterogeneity analysis considering two separate subsamples of girls and boys to investigate whether the effect of Raskin varies based on the gender of the child. Panel A of Table 4.2 reports the bivariate probit estimation results. The coefficient of the treatment effect (Raskin*Post)

[23]One limitation of the bivariate probit model is it assumes that the correlation between work and school (i.e. rho) is constant and hence the average marginal effects of each of the four joint outcomes take a restricted form. To show that this does not affect our results, we estimate a probit model for each of these outcomes. Results reported in Table C7.2 show that the coefficient of interest (Raskin*Post) continues to be significant. Therefore, this provides suggestive evidence that the assumption of constant rho does not significantly affect the results.

for girls is statistically insignificant at conventional levels for both work and school. This means Raskin has no significant effect on the probability of working and schooling for girls. When considering boys, Raskin has a negative impact on child labour, while no significant impact on schooling is observed.

Table 4.2: Effect of Raskin by gender.

Panel A - Bivariate Probit Estimates

	Girls		Boys	
	(1)	(2)	(3)	(4)
	Work	School	Work	School
Post	0.846**	-1.289***	1.389***	-0.948***
	(0.401)	(0.308)	(0.431)	(0.331)
Raskin	0.251	0.081	0.556**	-0.288*
	(0.274)	(0.172)	(0.257)	(0.155)
Raskin*Post	-0.333	0.254	-0.738**	0.152
	(0.326)	(0.202)	(0.299)	(0.221)
Rho	-0.378***		-0.238**	
	(0.100)		(0.093)	
Number of observations	2,150		2,159	

Panel B - Average Marginal Effects of Girls

	(5)	(6)	(7)	(8)
	Work only	School only	Both work & school	Idle
	(work=1 school=0)	(work=0 school=1)	(work=1 school=1)	(work=0 school=0)
Post	0.018**	-0.194***	0.035**	0.141***
	(0.009)	(0.043)	(0.017)	(0.036)
Raskin	0.001	-0.006	0.016	-0.011
	(0.003)	(0.028)	(0.016)	(0.019)
Raskin*Post	-0.005	0.049	-0.019	-0.025
	(0.004)	(0.033)	(0.021)	(0.021)

Panel C - Average Marginal Effects of Boys

	(9)	(10)	(11)	(12)
	Work only	School only	Both work & school	Idle
	(work=1 school=0)	(work=0 school=1)	(work=1 school=1)	(work=0 school=0)
Post	0.028**	-0.196***	0.080***	0.088***
	(0.012)	(0.050)	(0.027)	(0.033)
Raskin	0.008**	-0.070***	0.035**	0.027
	(0.003)	(0.025)	(0.016)	(0.016)
Raskin*Post	-0.009*	0.070**	-0.052**	-0.010
	(0.004)	(0.034)	(0.022)	(0.024)

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses, clustered at household and province levels. All estimations include the full set of control variables as given in Appendix Table C1, household, year and province fixed effects as well as the corresponding weights generated by CEM. See Tables C9 and C10 for comprehensive results.

Panels B and C of Table 4.2 present the average marginal effects (AME) of the estimated coefficients for girls and boys, respectively. In line with the bivariate probit model, Panel B shows that despite the expected direction of the effect, none of the probabilities of the four outcomes of work and school for girls are statistically significant at conventional levels. In contrast, for boys, Raskin significantly reduces the likelihood of engaging solely in work by 0.9 percentage points while increasing the probability of only attending school by seven percentage points. As a result, the probability of boys who are both working and schooling decreases by 5.2 percentage points. Taken together, this suggests that the effect of Raskin is heterogeneous. Specifically, it reduces work and increases schooling for boys while there is no impact on the outcomes of girls.

4.8 Robustness Checks

4.8.1 Testing Model Robustness

One common approach used in examining the model robustness is to check the sensitivity of the estimated treatment effects to the inclusion of observed controls (Oster, 2019). Therefore, we re-estimate the bivariate probit models by progressively including the control variables. Table 4.3 presents the results. The effect of Raskin on child labour remains consistently negative and significant in all specifications. Specification 1 reports the estimation results with only fixed effects. Controlling for child and household characteristics makes the effect even stronger in magnitude (specifications 2 and 3). Specification 4 provides the estimates from the original model with all covariates, as reported in Table 4.1. The stability of the treatment effect suggests that our results are robust to the choice of control variables. A similar pattern is also apparent for the subsamples of girls and boys (Panels B and C).

The finding that the treatment effect on child labour is smaller in specification one without any controls compared to the original specification with the full set of covariates (specification 4), also provides indicative evidence on the magnitude of omitted variable bias on the treatment effect. One of the key identification assumptions of matching is that both treatment and control units are similar in terms of any unobservable variables that could affect both the probability of participating in the program and the outcomes of interest (Gertler et al., 2011). Though it is argued that selection on observables could account for such unobservables to a certain extent, it is important to examine the nature of bias that could be induced by the presence of any unobservables (Datt & Uhe, 2018). Therefore, given that adding more controls are likely to increase the magnitude of the treatment effect as seen in Table 4.3, it can be inferred that if there are any unobservables, the direction of bias is likely to be negative implying larger treatment effect on child labour than the estimated effect. Furthermore, if there are still other unobservables (such as bribery, corruption or favouritism) that may produce a positive bias, it would have to be sufficiently strong to reverse the estimated negative impact of Raskin on child labour (Datt and Uhe, 2018).

Table 4.3: Model Robustness

Panel A -	Specification 1		Specification 2		Specification 3		Specification 4	
Full Sample	Work	School	Work	School	Work	School	Work	School
Post	1.056***	-0.021	1.090***	0.028	1.106***	-1.174***	1.096***	-1.145***
	(0.200)	(0.091)	(0.226)	(0.111)	(0.315)	(0.222)	(0.309)	(0.227)
Raskin	0.429**	-0.112	0.492**	-0.272**	0.386*	-0.161	0.403**	-0.096
	(0.171)	(0.085)	(0.197)	(0.112)	(0.197)	(0.115)	(0.196)	(0.117)
Raskin*Post	-0.451**	0.056	-0.466**	0.159	-0.491**	0.282*	-0.505**	0.206
	(0.203)	(0.113)	(0.230)	(0.139)	(0.233)	(0.148)	(0.232)	(0.152)
Household FE	Yes		Yes		Yes		Yes	
Individual FE	Yes		Yes		Yes		Yes	
Province FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
Child controls	No		Yes		Yes		Yes	
Household controls	No		No		Yes		Yes	
Parent controls	No		No		No		Yes	
Rho	-0.022		-0.225***		-0.231***		-0.254***	
	(0.059)		(0.065)		(0.069)		(0.066)	
Observations	4,370		4,370		4,309		4,309	

Table 4.3: *continued.*

Panel B - Girls	Specification 1		Specification 2		Specification 3		Specification 4	
	Work	School	Work	School	Work	School	Work	School
Post	0.771***	-0.073	0.867***	-0.078	0.821**	-1.334***	0.846**	-1.289***
	(0.244)	(0.152)	(0.264)	(0.150)	(0.378)	(0.307)	(0.401)	(0.308)
Raskin	0.220	0.003	0.293	-0.098	0.330	0.026	0.251	0.081
	(0.246)	(0.120)	(0.275)	(0.166)	(0.265)	(0.173)	(0.274)	(0.172)
Raskin*Post	-0.130	0.019	-0.191	0.199	-0.326	0.302	-0.333	0.254
	(0.280)	(0.171)	(0.312)	(0.198)	(0.315)	(0.201)	(0.326)	(0.202)
Household FE	Yes		Yes		Yes		Yes	
Individual FE	Yes		Yes		Yes		Yes	
Province FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
Child controls	No		Yes		Yes		Yes	
Household controls	No		No		Yes		Yes	
Parent controls	No		No		No		Yes	
Rho	-0.110		-0.342***		-0.345***		-0.378***	
	(0.079)		(0.096)		(0.102)		(0.100)	
Observations	2,177		2,177		2,150		2,150	

Panel C - Boys	Specification 1		Specification 2		Specification 3		Specification 4	
	Work	School	Work	School	Work	School	Work	School
Post	1.376***	0.066	1.372***	0.172	1.419***	-0.953***	1.389***	-0.948***
	(0.253)	(0.147)	(0.282)	(0.183)	(0.449)	(0.322)	(0.431)	(0.331)
Raskin	0.604***	-0.223*	0.671***	-0.431***	0.491*	-0.355**	0.556**	-0.288*
	(0.221)	(0.122)	(0.252)	(0.146)	(0.269)	(0.149)	(0.257)	(0.155)
Raskin*Post	-0.737***	0.035	-0.710**	0.049	-0.758**	0.204	-0.738**	0.152
	(0.261)	(0.163)	(0.300)	(0.205)	(0.316)	(0.215)	(0.299)	(0.221)
Household FE	Yes		Yes		Yes		Yes	
Individual FE	Yes		Yes		Yes		Yes	
Province FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
Child controls	No		Yes		Yes		Yes	
Household controls	No		No		Yes		Yes	
Parent controls	No		No		No		Yes	
Rho	0.033		-0.143		-0.163		-0.238**	
	(0.083)		(0.093)		(0.100)		(0.093)	
Observations	2,193		2,193		2,159		2,159	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include the corresponding weights generated by CEM.

4.8.2 Alternative Matching

In section 4.6.1, we matched the treated and control households on several household characteristics determined by a probit estimation. The covariates that were used for matching are place of residence, household size, dependency ratio, per capita expenditure, ownership of business, access to electricity, whether the household purchases water, uses firewood for cooking, uses the nearby river, land or sea as the toilet and poor sanitation. This selection was based on the variables that are statistically significant at 1% level. Despite the statistical significance of assets per capita, it was not used as a matching variable. This is because as continuous variables, inclusion of both assets per capita and per capita expenditure leads to poor matching outcomes. Therefore, as a robustness check, we consider assets per capita instead of per capita expenditure to examine whether the results are sensitive to the matched variables. The coarsened exact matching summaries presented in Tables C11 and C12 in Appendix show that CEM has produced a reasonable match where both the overall multivariate and univariate imbalances are reduced substantially in the post-match. However, compared to the matching summary reported in Table C4, the number of unmatched households in both control and treated groups is higher when assets per capita is used instead of per capita expenditure. Table 4.4 reports the results with new CEM weights. The results are qualitatively similar to those reported in Section 4.6, indicating the effect of Raskin on child labour and schooling is robust to the choice of matched variables.

Table 4.4: Bivariate probit estimates with alternative matching

	Full Sample		Girls		Boys	
Variables	(1)	(2)	(4)	(5)	(7)	(8)
	Work	School	Work	School	Work	School
Post treatment	1.204***	-0.854***	1.327***	-0.698*	1.389***	-0.899***
	(0.314)	(0.256)	(0.479)	(0.358)	(0.466)	(0.332)
Raskin	0.404*	-0.187	0.208	-0.115	0.666**	-0.285*
	(0.227)	(0.116)	(0.370)	(0.159)	(0.295)	(0.168)
Raskin*Post	-0.486*	0.061	-0.354	0.173	-0.760**	-0.216
	(0.258)	(0.163)	(0.405)	(0.225)	(0.346)	(0.236)
Rho	-0.403***		-0.368**		-0.582***	
	(0.083)		(0.144)		(0.132)	
Observations	3,532	3,532	1,805	1,805	1,727	1,727

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include the full set of control variables as given in Appendix Table C1, household, year and province fixed effects as well as the corresponding weights generated by CEM See Table C13 for comprehensive results.

4.9 Interpretation and Comparison with Related Literature

We find that Raskin is effective in decreasing child work for boys. However, its minimum or no effect on reducing child labour and increasing schooling, particularly of girls may be counter-intuitive at first. As an unconditional in-kind transfer, it is expected that the monetary benefit derived from it would generate an income effect leading to a reduction in the supply of child labour as well as an increase in schooling. Nevertheless, given limited empirical evidence on similar social protection tools that are unconditional by nature, our results are not contradictory. For instance, Guarcello et al. (2010) show that providing health insurance is effective only in reducing child work while having no impact in increasing children's participation in school in Guatemala. Therefore, as an unconditional in-kind transfer, the ability of Raskin to decrease the probability of work for boys specifically of those who are working and attending school simultaneously, by approximately 0.7 percentage points provides a useful policy insight on how food subsidies can indirectly influence the wellbeing of children.

Considering conditional in-kind transfers, studies such as de Hoop and Rosati (2014b), Kazianga et al. (2009) and Ravallion and Wodon (2000) all show that in-kind transfers such as food for education programs that are conditioned on school attendance are effective only in increasing schooling while having a minimum or no impact in reducing children's overall involvement in child labour activities. Interestingly, we find that the opposite is true in the context of an unconditional in-kind transfer such as a food subsidy which merits further discussion. Education is compulsory for Indonesian children aged seven to fifteen years. This means irrespective of the household's economic status parents are compelled to send their children to school. Therefore, receiving transfers, especially an unconditional one, may not provide the required incentive for the households to alter the decision of sending their children to school significantly. Compared to girls, boys generally have higher participation in market work, meaning a lower likelihood of attending school (Edmonds, 2007). This justifies as to why Raskin only leads to a reduction in child work for boys, as boys are more likely to involve in wage work which is often considered to be a worse form of child labour.

The limited effect of the Raskin program on the supply of child labour and schooling may be due to several reasons. First, the benefit of the subsidy, which accounts for about five per cent of the monthly consumption expenditure of poor households, may not be sufficient to keep children out of the labour market. Particularly, to achieve greater impacts on child labour, income transfers should be of sufficiently sizeable value (Datt & Uhe, 2018). However, in view of Banerjee and Duflo (2011), the poor usually do not do what is in their best interest even if they could afford to do so. This means rather than utilising the income effect that they receive from the rice subsidy to forgo the income earned from child labour, they may spend it on less important things such as festivals and family events. Second, the limited effect of the Raskin program can also be attributed to the behavioural constraints of the poor such as small inconveniences (Banerjee & Duflo, 2011) that restrict them to gain the full benefit of the subsidy. Around two to three per cent of those who are eligible to receive Raskin have refused the receipt of the subsidy at least once in a given year, due to reasons such as inability to go on the allocated day, lack of time or long distance to the distribution centre. Third, there may be issues of accurate targeting of the program leading to both inclusion and exclusion errors. It is stated that redistribution programs in less developed countries often leak due to various reasons such as targeting method used, take up problems, corruption and bribes (Banerjee et al., 2016; Currie & Gahvari, 2008; Trimmer et al., 2018). According to Banerjee et al. (2016), though the government of Indonesia spends over US$ 1.5 billion a year on the Raskin program, less than half of the rice was actually reaching the intended households. Therefore, this study also underscores the importance of accurate targeting of government social protection programs so as to achieve the ultimate goal of poverty reduction.

4.10 Conclusion and Policy Implications

Child labour continues to be a problem of the developing world, where nine out of every ten children in child labour are in the regions of Africa, Asia and Pacific. Therefore, there is a compelling need for evidence-based interventions on child labour to inform policy responses. Since child labour is strongly related with and determined by poverty, social protection programs are a potential source of mitigation. Though there is ample evidence on the impact of cash transfers on child labour, evidence on the effect of other social protection tools, particularly of in-kind transfers is limited. This paper addresses this empirical gap by examining the impacts of an unconditional in-kind transfer - a subsidised food program on child work as well as schooling. To this end, we consider the Raskin program, which is the largest subsidised rice program in Indonesia.

We find that in general, a food subsidy is not effective in reducing the labour supply of children and schooling for girls. However, the program has a strong effect in inducing boys who are both working and attending school to decrease child labour. Specifically, a subsidy on a staple food like rice can lead to a decrease in the probability of work for boys by 0.9 percentage points.

In line with previous studies on conditional in-kind transfers and child labour, our results are not contradictory. In fact, as an unconditional in-kind transfer, the ability of a food subsidy to decrease child labour of boys in a developing country provides an important policy implication on how social protection tools can indirectly influence the wellbeing of children.

The minimum effect of the subsidy on child labour and schooling may be due to several reasons. Among them, the size of the subsidy, as well as targeting issues leading to considerable leakages are prominent. Therefore, the findings of our study indicate that to reap the maximum benefits of pro-poor programs such as subsidised food programs, it is vital to design such programs in a manner that maximises its reach and intensity. This would inevitably have a considerable impact on the welfare of poor households and thereby ensure child wellbeing.

Appendix C

Table C1: Variable Description

Variable	Description
Child-working	=1 if the child has ever worked
Child-schooling	=1 if the child is still in school
Raskin	=1 if the household has ever bought rice from Raskin (during the past year)
Child Characteristics	
Child gender	=1 if the child is a female
Child-age	Age of the child
Child-age2	Age of the child squared
Child-religion-Islam	=1 if the child's religion is Islam
Household Characteristics	
Household size	The number of members in the household
Dependency ratio	The ratio of the number of household members aged below 14 and above 65 years to the number of working members aged 15 - 64 years
HHH-female	=1 if the household head is a female
Urban	=1 if the household is in an urban area
Own business	=1 if the household has its own farm business
Own farm land	=1 if the household has its own farm land
Per capita expenditure (PCE) (ln)	Logarithm of monthly per capita expenditure
Assets per capita (ln)	Logarithm of household assets per capita
Electricity	=1 if the household has access to electricity
Water	=1 if the household purchases water
Toilet-river/land/sea	=1 if the household does not have proper toilet facilities
Cook-firewood	=1 if the household uses firewood as the main source of energy for cooking
Poor sanitation	=1 if the household has poor sanitation
Parent Characteristics	
Mother-age	Age of the mother
Father-age	Age of the father
Mother-married	=1 if the mother is married
Mother-paid occupation	=1 if the mother is occupied in a paid occupation
Father-paid occupation	=1 if the father is occupied in a paid occupation
Mother - elementary	=1 if the mother has completed elementary school
Mother - junior	=1 if the mother has completed junior school
Mother -senior	=1 if the mother has completed senior school
Mother - tertiary	=1 if the mother has completed tertiary education
Father - elementary	=1 if the father has completed elementary school
Father - junior	=1 if the father has completed junior school
Father - senior	=1 if the father has completed senior school
Father - tertiary	=1 if the father has completed tertiary education
Mother - highest edu	=1 if the mother has completed the highest level of education
Father - highest edu	=1 if the father has completed the highest level of education
Provincial Dummies	Seperate indicator variables for each of the following provinces: North Sumarta, West Sumarta, South Sumarta, Lampung, Jakarta, West Java, Central Java, Yogyakarta, East Java, Bali, West Nusa Tenggara, South Sulawesi and South Kalimantan

Table C2: Summary Statistics

Variables	Full Sample		Control Group Raskin = 0		Treatment Group Raskin = 1		Mean Difference
	Mean	SD	Mean	SD	Mean	SD	
Child-working	0.08	0.26	0.06	0.24	0.08	0.28	0.02***
Child-still in school	0.83	0.38	0.84	0.37	0.82	0.38	-0.02***
Child Characteristics							
Child gender	0.49	0.50	0.48	0.50	0.49	0.50	0.01
Child-age	9.52	2.88	9.44	2.88	9.56	2.88	0.13***
Child-religion-Islam	0.90	0.29	0.86	0.35	0.93	0.26	0.07***
Household Characteristics							
Urban	0.48	0.50	0.66	0.47	0.40	0.49	-0.26***
Household size	5.41	1.87	5.41	1.87	5.41	1.86	0.00
Dependency ratio	1.13	0.70	1.12	0.65	1.14	0.73	0.02**
HHH female	0.12	0.33	0.10	0.30	0.13	0.34	0.03***
Assets per capita (ln)	15.20	1.92	15.97	1.99	14.85	1.78	-1.12***
Per capita expenditure (ln)	12.49	1.20	12.98	1.26	12.27	1.10	-0.71***
Own business	0.43	0.49	0.46	0.50	0.41	0.49	-0.05***
Own farmland	0.32	0.47	0.28	0.45	0.34	0.47	0.07***
Electricity	0.92	0.27	0.95	0.21	0.91	0.29	-0.05***
Water	0.27	0.44	0.39	0.49	0.22	0.41	-0.17***
Cook - firewood	0.38	0.49	0.19	0.39	0.46	0.50	0.28***
Toilet - river/land/sea	0.22	0.41	0.09	0.28	0.28	0.45	0.20***
Poor sanitation	0.23	0.42	0.17	0.38	0.25	0.44	0.08***
Parent Characteristics							
Mother age	36.62	6.81	36.81	6.17	36.54	7.09	-0.27**
Father - age	41.40	7.99	41.18	7.02	41.51	8.42	0.33**
Mother married	0.97	0.18	0.97	0.17	0.96	0.18	-0.01*
Mother - paid occupation	0.42	0.49	0.39	0.49	0.43	0.50	0.04***
Father - paid occupation	0.87	0.34	0.88	0.33	0.87	0.34	-0.01**
Mother - elementary	0.47	0.50	0.28	0.45	0.56	0.50	0.28***
Mother - junior	0.18	0.39	0.18	0.38	0.18	0.39	0.00
Mother -senior	0.20	0.40	0.35	0.48	0.13	0.33	-0.22***
Mother - tertiary	0.06	0.24	0.15	0.36	0.02	0.13	-0.13***
Father - elementary	0.44	0.50	0.24	0.42	0.53	0.50	0.30***
Father - junior	0.16	0.36	0.15	0.36	0.16	0.37	0.01
Father - senior	0.25	0.43	0.38	0.49	0.18	0.39	-0.20***
Father - tertiary	0.08	0.27	0.19	0.39	0.03	0.17	-0.16***
Mother - highest edu	0.61	0.49	0.74	0.44	0.55	0.50	-0.19***
Father - highest edu	0.61	0.49	0.73	0.44	0.55	0.50	-0.19***

Notes: The significant values are obtained from the test of significance in the difference of means between the treatment and control groups for each of the variables. The significant differences are at least at 5% level.

Table C3: Probit Estimation for Matching

Variables	Coefficient
Urban	-0.309***
	(0.045)
Household size	-0.077***
	(0.009)
Dependency ratio	-0.073***
	(0.025)
HHH-female	0.003
	(0.064)
Assets per capita (ln)	-0.120***
	(0.014)
Per capita expenditure (ln)	-0.238***
	(0.033)
Own business	0.104***
	(0.039)
Own farm land	-0.086*
	(0.046)
Electricity	0.202***
	(0.056)
Water	-0.366***
	(0.044)
Cook-firewood	0.141***
	(0.047)
Toilet-river/land/sea	0.355***
	(0.041)
Poor sanitation	0.172***
	(0.045)
Constant	5.107***
	(0.370)
Number of observations	5,773

Notes: Robust standard errors in parentheses, clustered at household and province level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Estimation is based on wave 2 data.

Table C4: Coarsened Exact Matching Summary

	Control (Raskin = 0)	Treatment (Raskin = 1)
All	1972	3899
Matched	910	1071
Unmatched	1062	2828

Table C5: Covariate Balance

Pre-match multivariate L1 distance: 0.9091

	Pre-match univariate imbalance		Sample mean	
	L1	Mean difference	Control (Raskin=0)	Treatment (Raskin = 1)
Urban	0.238	-0.238	0.657	0.396
Household size	0.091	-0.347	5.414	5.412
Dependency ratio	0.094	0.030	1.120	1.140
Per capita expenditure (ln)	0.251	-0.394	12.978	12.270
Own business	0.025	-0.025	0.460	0.414
Electricity	0.080	-0.080	0.954	0.906
Water	0.143	-0.143	0.387	0.219
Cook firewood	0.231	0.231	0.190	0.465
Toilet-river/land/sea	0.228	0.228	0.086	0.281
Poor sanitation	0.094	0.094	0.175	0.255

Post-match multivariate L1 distance: 0.6821

	Post-match univariate imbalance		Sample mean	
	L1	Mean difference	Control (Raskin=0)	Treatment (Raskin = 1)
Urban	0.000	0.000	0.378	0.378
Household size	0.012	0.010	5.156	5.166
Dependency ratio	0.007	0.002	1.085	1.087
Per capita expenditure (ln)	0.125	-0.021	11.195	11.174
Own business	0.000	0.000	0.323	0.323
Electricity	0.000	0.000	0.859	0.859
Water	0.000	0.000	0.102	0.102
Cook firewood	0.000	0.000	0.506	0.506
Toilet-river/land/sea	0.000	0.000	0.256	0.256
Poor sanitation	0.000	0.000	0.120	0.120

Table C6: Bivariate Probit Model with and without CEM weights

Variables	DD without CEM weights		DD with CEM weights	
	(1)	(2)	(3)	(4)
	Work	School	Work	School
Post	1.089***	-0.640***	1.096***	-1.145***
	(0.128)	(0.083)	(0.309)	(0.227)
Raskin	0.250**	-0.142**	0.403**	-0.096
	(0.108)	(0.063)	(0.196)	(0.117)
Raskin*Post	-0.250**	0.217***	-0.505**	0.206
	(0.115)	(0.068)	(0.232)	(0.152)
Child Characteristics				
Child gender	-0.101***	0.105***	-0.197**	0.154**
	(0.029)	(0.027)	(0.083)	(0.072)
Child age	0.206***	2.678***	0.143	2.658***
	(0.048)	(0.042)	(0.146)	(0.127)
Child age2	-0.000	-0.130***	0.005	-0.128***
	(0.002)	(0.002)	(0.007)	(0.006)
Child religion Islam	-0.223***	-0.213***	-0.360*	-0.432**
	(0.068)	(0.069)	(0.203)	(0.201)
Household Characteristics				
Urban	-0.101**	0.036	-0.119	0.070
	(0.040)	(0.036)	(0.125)	(0.098)
Household size	0.014	-0.018*	0.072**	0.002
	(0.009)	(0.009)	(0.029)	(0.024)
Dependency ratio	0.096***	-0.048**	0.105	-0.079
	(0.023)	(0.021)	(0.069)	(0.064)
HHH female	-0.047	-0.020	0.009	-0.057
	(0.060)	(0.051)	(0.154)	(0.129)
Assets per capita (ln)	-0.021*	0.039***	-0.072*	0.060*
	(0.013)	(0.011)	(0.039)	(0.033)
Per capita expenditure	0.062**	0.162***	0.184**	0.365***
	(0.030)	(0.028)	(0.093)	(0.087)
Own business	0.436***	0.037	0.249***	0.062
	(0.033)	(0.030)	(0.090)	(0.079)
Own farmland	0.208***	0.102***	0.210**	0.133
	(0.036)	(0.034)	(0.098)	(0.087)
Electricity	-0.108*	0.419***	0.072	0.101
	(0.064)	(0.058)	(0.165)	(0.143)
Water	-0.009	-0.052	-0.213*	-0.100
	(0.040)	(0.033)	(0.124)	(0.096)
Cook firewood	0.100**	-0.133***	0.290**	-0.004
	(0.041)	(0.036)	(0.128)	(0.101)
Toilet - river/land/sea	0.082*	-0.112***	-0.171	-0.179*
	(0.042)	(0.038)	(0.152)	(0.100)
Poor sanitation	0.096**	-0.040	0.138	-0.089
	(0.039)	(0.034)	(0.140)	(0.097)
Parent Characteristics				
Mother age	-0.002	0.003	-0.012	-0.003
	(0.004)	(0.004)	(0.011)	(0.009)
Father age	0.002	0.000	0.003	0.000
	(0.003)	(0.003)	(0.009)	(0.008)
Mother married	0.036	-0.079	-0.289	-0.137
	(0.093)	(0.100)	(0.272)	(0.260)
Mother paid occupation	0.177***	-0.023	0.060	-0.068
	(0.036)	(0.033)	(0.101)	(0.085)
Father paid occupation	-0.040	0.015	0.146	-0.253*
	(0.054)	(0.048)	(0.165)	(0.130)

Mother - elementary	-0.095	0.294***	-0.342*	0.391***
	(0.065)	(0.061)	(0.185)	(0.132)
Mother-junior	-0.116	0.379***	-0.383*	0.638***
	(0.084)	(0.073)	(0.232)	(0.173)
Mother - senior	-0.113	0.250***	-0.207	0.598***
	(0.091)	(0.077)	(0.281)	(0.185)
Mother - tertiary	-0.273**	0.189**	-0.462	0.796**
	(0.123)	(0.096)	(0.427)	(0.329)
Father - elementary	-0.084	0.152**	0.346*	0.347**
	(0.074)	(0.066)	(0.198)	(0.154)
Father - junior	-0.096	0.293***	0.388	0.336*
	(0.088)	(0.077)	(0.237)	(0.189)
Father - senior	-0.206**	0.246***	-0.088	0.184
	(0.094)	(0.077)	(0.279)	(0.191)
Father-tertiary	-0.474***	0.240***	-0.671*	-0.103
	(0.124)	(0.092)	(0.343)	(0.246)
Mother - highest edu	-0.084*	0.149***	0.317**	0.118
	(0.045)	(0.038)	(0.124)	(0.097)
Father - highest edu	-0.056	0.107***	-0.075	-0.004
	(0.043)	(0.036)	(0.110)	(0.098)
Constant	-4.889***	-14.388***	-4.641***	-16.136***
	(0.473)	(0.435)	(1.347)	(1.421)
Rho	-0.269***		-0.254***	
	(0.026)		(0.066)	
Observations	23,028		4,309	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include household, year and province fixed effects as well as the corresponding weights generated by CEM.

Table C7.1: Average Marginal Effects of the Bivariate Probit Model

Variables	Work only (work=1 school=0)	School only (work=0 school=1)	Both work & school (work=1 school=1)	Idle (work=0 school=0)
Post	0.025***	-0.204***	0.058***	0.121***
	(0.009)	(0.034)	(0.018)	(0.025)
Raskin	0.005**	-0.040**	0.028**	0.008
	(0.002)	(0.020)	(0.013)	(0.013)
Raskin*Post	-0.007**	0.062**	-0.036**	-0.019
	(0.003)	(0.026)	(0.018)	(0.017)
Child Characteristics				
Child gender	-0.003***	0.033***	-0.013**	-0.016*
	(0.001)	(0.010)	(0.006)	(0.008)
Child age	0.009***	0.038***	0.013***	-0.060***
	(0.001)	(0.003)	(0.002)	(0.002)
Child religion Islam	0.001	-0.013	-0.036*	0.048***
	(0.003)	(0.031)	(0.021)	(0.019)
Household Characteristics				
Urban	-0.002	0.017	-0.008	-0.007
	(0.002)	(0.015)	(0.009)	(0.011)
Household size	0.001*	-0.005	0.005**	-0.001
	(0.000)	(0.004)	(0.002)	(0.003)
Dependency ratio	0.002*	-0.017*	0.007	0.008
	(0.001)	(0.010)	(0.005)	(0.007)
HHH female	0.001	-0.007	0.000	0.007
	(0.002)	(0.019)	(0.012)	(0.016)
Assets per capita (ln)	-0.001**	0.012**	-0.005	-0.006
	(0.001)	(0.005)	(0.003)	(0.004)
Per capita expenditure	-0.002	0.029**	0.017**	-0.044***
	(0.001)	(0.014)	(0.007)	(0.010)
Own business	0.002	-0.012	0.020***	-0.010
	(0.001)	(0.012)	(0.007)	(0.009)
Own farmland	0.001	-0.001	0.017**	-0.017*
	(0.001)	(0.013)	(0.008)	(0.010)
Electricity	-0.000	0.007	0.006	-0.013
	(0.002)	(0.022)	(0.011)	(0.018)
Water	-0.001	0.003	-0.015**	0.014
	(0.001)	(0.015)	(0.008)	(0.012)
Cook firewood	0.003*	-0.023	0.022**	-0.002
	(0.002)	(0.016)	(0.010)	(0.012)
Toilet - river/land/sea	-0.000	-0.010	-0.014	0.023*
	(0.002)	(0.016)	(0.010)	(0.013)
Poor sanitation	0.002	-0.021	0.010	0.009
	(0.002)	(0.017)	(0.011)	(0.012)
Parent Characteristics				
Mother age	-0.000	0.001	-0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.001)
Father age	0.000	-0.000	0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)
Mother married	-0.001	0.009	-0.025	0.018
	(0.004)	(0.042)	(0.025)	(0.028)
Mother paid occupation	0.001	-0.013	0.004	0.007
	(0.001)	(0.013)	(0.008)	(0.010)
Father paid occupation	0.004*	-0.039**	0.008	0.027*
	(0.002)	(0.019)	(0.012)	(0.014)
Mother - elementary	-0.007***	0.071***	-0.021	-0.042***
	(0.003)	(0.021)	(0.014)	(0.016)

Mother-junior	-0.007***	0.091***	-0.021	-0.063***
	(0.002)	(0.021)	(0.013)	(0.015)
Mother - senior	-0.006***	0.077***	-0.010	-0.061***
	(0.002)	(0.027)	(0.018)	(0.017)
Mother - tertiary	-0.006***	0.104***	-0.024	-0.073***
	(0.002)	(0.034)	(0.020)	(0.025)
Father - elementary	0.000	0.014	0.030*	-0.044**
	(0.003)	(0.026)	(0.016)	(0.018)
Father - junior	0.000	0.001	0.038	-0.039**
	(0.003)	(0.033)	(0.025)	(0.018)
Father - senior	-0.002	0.027	-0.005	-0.020
	(0.003)	(0.030)	(0.020)	(0.021)
Father-tertiary	-0.004*	0.022	-0.036***	0.018
	(0.002)	(0.034)	(0.012)	(0.032)
Mother - highest edu	0.002	-0.010	0.025***	-0.017
	(0.002)	(0.015)	(0.010)	(0.011)
Father - highest edu	-0.001	0.005	-0.006	0.001
	(0.001)	(0.015)	(0.008)	(0.011)
Observations	4,309	4,309	4,309	4,309

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include household, year and province fixed effects as well as the corresponding weights generated by CEM. Marginal effects represent the percentage change in probability of an outcome given a unitary increase in a continuous variable or change from 0 to 1 for binary variable.

Table C7.2: Average Marginal Effects of the Probit Model - DD with CEM weights

Variables	Work only (work = 1 school = 0)	School only (work = 0 school = 1)	Both work & school (work = 1 school = 1)	Idle (work = 0 school = 0)
Post	0.079***	-0.142***	0.086***	0.159***
	(0.025)	(0.029)	(0.025)	(0.030)
Raskin	0.033**	-0.012	0.031*	0.009
	(0.015)	(0.015)	(0.017)	(0.014)
Raskin*Post	-0.043**	0.025	-0.045*	-0.028
	(0.020)	(0.019)	(0.023)	(0.018)
Observations	4,309	4,309	4,309	4,309

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include the full set of control variables as given in Appendix Table C1, household, year and province fixed effects as well as the corresponding weights generated by CEM.

Table C8: Actual and Predicted Probabilities

	Work only (work = 1 school = 0)	School only (work = 0 school = 1)	Both work & school (work = 1 school = 1)	Idle (work = 0 school = 0)
Sample Mean	0.012	0.762	0.063	0.162
Predicted Probability	0.010	0.768	0.057	0.166
Number of observations	284	17939	1488	3820

Note: Predicted probability represents the predictive margins of a given outcome.

Table C9: Bivariate Probit Model by Gender

Variables	Girls		Boys	
	(1)	(2)	(3)	(4)
	Work	School	Work	School
Post	0.846**	-1.289***	1.389***	-0.948***
	(0.401)	(0.308)	(0.431)	(0.331)
Raskin	0.251	0.081	0.556**	-0.288*
	(0.274)	(0.172)	(0.257)	(0.155)
Raskin*Post	-0.333	0.254	-0.738**	0.152
	(0.326)	(0.202)	(0.299)	(0.221)
Child Characteristics				
Child age	0.210	2.637***	0.094	2.839***
	(0.220)	(0.181)	(0.212)	(0.154)
Child age2	0.000	-0.127***	0.009	-0.137***
	(0.010)	(0.009)	(0.010)	(0.008)
Child religion Islam	-0.013	-0.331	-0.586**	-0.349
	(0.310)	(0.294)	(0.241)	(0.302)
Household Characteristics				
Urban	0.006	0.057	-0.167	0.071
	(0.154)	(0.124)	(0.175)	(0.143)
Household size	0.049	0.002	0.102**	0.003
	(0.038)	(0.035)	(0.040)	(0.033)
Dependency ratio	0.098	-0.029	0.117	-0.148*
	(0.096)	(0.099)	(0.095)	(0.078)
HHH female	0.184	0.046	-0.163	-0.206
	(0.192)	(0.194)	(0.250)	(0.190)
Assets per capita (ln)	0.003	0.046	-0.158***	0.057
	(0.058)	(0.047)	(0.050)	(0.043)
Per capita expenditure	0.101	0.397***	0.333**	0.332***
	(0.125)	(0.120)	(0.140)	(0.115)
Own business	0.546***	-0.031	0.055	0.160
	(0.128)	(0.105)	(0.131)	(0.119)
Own farmland	0.178	0.145	0.205	0.070
	(0.134)	(0.121)	(0.140)	(0.120)
Electricity	0.145	0.172	0.082	0.004
	(0.245)	(0.200)	(0.218)	(0.192)
Water	-0.028	0.063	-0.354*	-0.338**
	(0.156)	(0.135)	(0.190)	(0.139)
Cook firewood	0.429***	0.248*	0.290*	-0.262*
	(0.144)	(0.144)	(0.170)	(0.144)
Toilet - river/land/sea	0.039	-0.448***	-0.423**	0.094
	(0.172)	(0.143)	(0.199)	(0.137)
Poor sanitation	0.068	-0.120	0.163	-0.079
	(0.152)	(0.131)	(0.166)	(0.142)
Parent Characteristics				
Mother age	-0.012	-0.009	-0.018	-0.002
	(0.014)	(0.012)	(0.016)	(0.014)
Father age	-0.000	0.001	0.008	-0.001
	(0.011)	(0.011)	(0.013)	(0.011)
Mother married	-0.737**	0.081	0.179	-0.239
	(0.327)	(0.409)	(0.421)	(0.311)
Mother paid occupation	0.096	0.084	0.001	-0.207*
	(0.144)	(0.121)	(0.139)	(0.115)
Father paid occupation	0.027	-0.452**	0.224	-0.137
	(0.239)	(0.204)	(0.200)	(0.169)
Mother - elementary	-0.439*	0.365*	-0.371	0.389**
	(0.253)	(0.197)	(0.241)	(0.171)

Mother-junior	-0.695**	0.361	-0.400	0.837***
	(0.327)	(0.252)	(0.320)	(0.230)
Mother - senior	-0.459	0.664**	-0.136	0.560**
	(0.348)	(0.280)	(0.389)	(0.242)
Mother - tertiary	-0.688	0.782**	-0.918	1.034**
	(0.454)	(0.354)	(0.799)	(0.426)
Father - elementary	0.301	0.497**	0.415*	0.265
	(0.287)	(0.205)	(0.245)	(0.206)
Father - junior	-0.010	0.681***	0.518*	0.082
	(0.350)	(0.262)	(0.295)	(0.255)
Father - senior	0.188	0.313	-0.367	0.101
	(0.369)	(0.257)	(0.372)	(0.264)
Father-tertiary	0.064	0.137	-5.616***	-0.248
	(0.419)	(0.295)	(0.425)	(0.335)
Mother - highest edu	0.334*	0.056	0.357**	0.160
	(0.185)	(0.132)	(0.170)	(0.134)
Father - highest edu	-0.117	-0.010	-0.077	0.037
	(0.153)	(0.126)	(0.161)	(0.144)
Constant	-5.317***	-15.643***	-4.503**	-17.373***
	(1.822)	(2.071)	(2.161)	(1.803)
Rho	-0.378***		-0.238**	
	(0.100)		(0.093)	
Observations	2,150	2,150	2,159	2,159

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include household, year and province fixed effects as well as the corresponding weights generated by CEM.

Table C10: Average Marginal Effects by Gender

	Girls				Boys			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Work only	School only	Both	Idle	Work only	School only	Both	Idle
	(work=1	(work=0	(work=1	(work=0	(work=1	(work=0	(work=1	(work=0
	school=0)	school=1)	school=1)	school=0)	school=0)	school=1)	school=1)	school=0)
Post	0.018**	-0.194***	0.035**	0.141***	0.028**	-0.196***	0.080***	0.088***
	(0.009)	(0.043)	(0.017)	(0.036)	(0.012)	(0.050)	(0.027)	(0.033)
Raskin	0.001	-0.006	0.016	-0.011	0.008**	-0.070***	0.035**	0.027
	(0.003)	(0.028)	(0.016)	(0.019)	(0.003)	(0.025)	(0.016)	(0.016)
Raskin*Post	-0.005	0.049	-0.019	-0.025	-0.009*	0.070**	-0.052**	-0.010
	(0.004)	(0.033)	(0.021)	(0.021)	(0.004)	(0.034)	(0.022)	(0.024)
Child characteristics								
Child age	0.006***	0.039***	0.009***	-0.055***	0.011***	0.036***	0.015***	-0.063***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)
Child religion Islam	0.002	-0.033	-0.003	0.034	-0.002	0.018	-0.057**	0.041
	(0.003)	(0.035)	(0.021)	(0.028)	(0.005)	(0.040)	(0.026)	(0.028)
Household characteristics								
Urban	-0.000	0.006	0.001	-0.006	-0.002	0.020	-0.011	-0.006
	(0.002)	(0.018)	(0.010)	(0.014)	(0.002)	(0.021)	(0.012)	(0.016)
Household size	0.000	-0.003	0.003	-0.001	0.001*	-0.007	0.007**	-0.001
	(0.000)	(0.005)	(0.002)	(0.004)	(0.001)	(0.005)	(0.003)	(0.004)
Dependency ratio	0.001	-0.009	0.006	0.002	0.003**	-0.025**	0.007	0.015*
	(0.001)	(0.013)	(0.006)	(0.011)	(0.001)	(0.012)	(0.007)	(0.009)
HHH female	0.001	-0.008	0.013	-0.007	0.001	-0.013	-0.013	0.026
	(0.003)	(0.026)	(0.015)	(0.021)	(0.003)	(0.027)	(0.016)	(0.024)
Assets per capita (ln)	-0.000	0.005	0.001	-0.005	-0.002***	0.018***	-0.011***	-0.005
	(0.001)	(0.007)	(0.004)	(0.005)	(0.001)	(0.006)	(0.004)	(0.005)
Per capita expenditure	-0.002	0.038**	0.010	-0.045***	-0.000	0.013	0.028***	-0.041***
	(0.002)	(0.017)	(0.008)	(0.013)	(0.002)	(0.018)	(0.010)	(0.013)
Own business	0.005***	-0.040**	0.036***	-0.002	-0.001	0.014	0.006	-0.018
	(0.002)	(0.015)	(0.009)	(0.011)	(0.002)	(0.017)	(0.010)	(0.013)
Own farmland	0.000	0.004	0.013	-0.017	0.001	-0.007	0.016	-0.010
	(0.002)	(0.017)	(0.009)	(0.013)	(0.002)	(0.017)	(0.010)	(0.013)
Electricity	-0.000	0.012	0.010	-0.021	0.001	-0.005	0.006	-0.001
	(0.003)	(0.030)	(0.013)	(0.024)	(0.003)	(0.028)	(0.015)	(0.022)
Water	-0.001	0.009	-0.001	-0.007	-0.000	-0.019	-0.026**	0.045**
	(0.002)	(0.019)	(0.010)	(0.014)	(0.003)	(0.022)	(0.010)	(0.018)
Cook firewood	0.002	-0.001	0.031***	-0.031*	0.006**	-0.051**	0.018	0.027
	(0.002)	(0.020)	(0.010)	(0.016)	(0.002)	(0.022)	(0.013)	(0.017)
Toilet - river/land/sea	0.005	-0.057**	-0.002	0.054***	-0.005**	0.038**	-0.027**	-0.007
	(0.003)	(0.022)	(0.011)	(0.018)	(0.002)	(0.019)	(0.012)	(0.015)
Poor sanitation	0.002	-0.018	0.003	0.013	0.003	-0.021	0.011	0.007
	(0.002)	(0.019)	(0.010)	(0.015)	(0.003)	(0.021)	(0.013)	(0.016)
Parent characteristics								
Mother age	-0.000	-0.000	-0.001	0.001	-0.000	0.001	-0.001	0.000
	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.002)
Father age	-0.000	0.000	0.000	-0.000	0.000	-0.001	0.001	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Mother married	-0.009	0.071	-0.061*	-0.001	0.004	-0.038	0.010	0.024
	(0.009)	(0.062)	(0.034)	(0.043)	(0.005)	(0.046)	(0.028)	(0.032)
Mother-occupation	0.000	0.003	0.007	-0.010	0.002	-0.023	-0.002	0.023*
	(0.002)	(0.017)	(0.009)	(0.013)	(0.002)	(0.017)	(0.010)	(0.013)
Father-occupation	0.004	-0.049*	-0.002	0.047**	0.003	-0.031	0.014	0.013
	(0.003)	(0.026)	(0.015)	(0.020)	(0.003)	(0.024)	(0.013)	(0.018)
Mother - elementary	-0.007**	0.068**	-0.025	-0.036*	-0.008**	0.070***	-0.022	-0.040**
	(0.003)	(0.029)	(0.016)	(0.021)	(0.004)	(0.026)	(0.017)	(0.019)

Mother-junior	-0.006***	0.071**	-0.031***	-0.034	-0.008***	0.107***	-0.021	-0.078***
	(0.002)	(0.028)	(0.012)	(0.024)	(0.002)	(0.025)	(0.019)	(0.019)
Mother - senior	-0.006***	0.088***	-0.021	-0.061**	-0.006**	0.067*	-0.005	-0.056**
	(0.002)	(0.029)	(0.015)	(0.024)	(0.003)	(0.035)	(0.027)	(0.022)
Mother - tertiary	-0.006***	0.101***	-0.028**	-0.067***	-0.009***	0.138***	-0.041*	-0.088***
	(0.002)	(0.030)	(0.014)	(0.025)	(0.002)	(0.039)	(0.025)	(0.028)
Father - elementary	-0.001	0.035	0.024	-0.057**	0.001	-0.001	0.034*	-0.034
	(0.003)	(0.033)	(0.020)	(0.022)	(0.004)	(0.032)	(0.018)	(0.023)
Father - junior	-0.004**	0.066*	0.004	-0.065***	0.004	-0.036	0.046	-0.014
	(0.002)	(0.035)	(0.023)	(0.021)	(0.005)	(0.042)	(0.030)	(0.026)
Father - senior	-0.001	0.019	0.016	-0.034	-0.004	0.035	-0.023	-0.008
	(0.003)	(0.040)	(0.029)	(0.024)	(0.004)	(0.039)	(0.021)	(0.029)
Father-tertiary	-0.001	0.010	0.005	-0.015	-0.010***	0.031	-0.063***	0.042
	(0.004)	(0.045)	(0.029)	(0.030)	(0.002)	(0.047)	(0.006)	(0.047)
Mother - highest edu	0.002	-0.015	0.022*	-0.009	0.002	-0.009	0.028**	-0.021
	(0.002)	(0.019)	(0.012)	(0.014)	(0.002)	(0.020)	(0.013)	(0.015)
Father - highest edu	-0.001	0.006	-0.007	0.002	-0.001	0.010	-0.005	-0.003
	(0.002)	(0.018)	(0.010)	(0.014)	(0.002)	(0.021)	(0.012)	(0.016)
Observations	2,150	2,150	2,150	2,150	2,159	2,159	2,159	2,159

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses, clustered at household and province levels. All estimations include household, year and province fixed effects as well as the corresponding weights generated by CEM. Marginal effects represent the percentage change in probability of an outcome given a unitary increase in a continuous variable or change from 0 to 1 for binary variable.

Table C11: Coarsened Exact Matching Summary

	Control (Raskin=0)	Treatment (Raskin=1)
All	1972	3899
Matched	720	865
Unmatched	1252	3034

Table C12: Covariate Balance

Pre-match multivariate L1 distance: 0.8999

	Pre-match univariate imbalance		Sample mean	
	L1	Mean difference	Control (Raskin=0)	Treatment (Raskin=1)
Urban	0.237	-0.237	0.657	0.396
Household size	0.088	-0.347	5.414	5.412
Dependency ratio	0.092	0.029	1.120	1.140
Assets per capita (ln)	0.235	-0.787	15.974	14.85
Own business	0.023	-0.023	0.460	0.414
Electricity	0.080	-0.080	0.954	0.906
Water	0.140	-0.140	0.387	0.219
Cook firewood	0.230	0.230	0.190	0.465
Toilet-river/land/sea	0.225	0.225	0.086	0.281
Poor sanitation	0.092	0.092	0.175	0.255

Post-match univariate imbalance: 0.6106

	Post-match univariate imbalance		Sample mean	
	L1	Mean difference	Control (Raskin=0)	Treatment (Raskin=1)
Urban	0.000	0.000	0.377	0.377
Household size	0.007	0.001	5.099	5.101
Dependency ratio	0.004	0.000	1.117	1.117
Assets per capita (ln)	0.131	-0.025	14.276	14.251
Own business	0.000	0.000	0.323	0.323
Electricity	0.000	0.000	0.851	0.851
Water	0.000	0.000	0.113	0.113
Cook firewood	0.000	0.000	0.473	0.473
Toilet-river/land/sea	0.000	0.000	0.257	0.257
Poor sanitation	0.000	0.000	0.081	0.081

Table C13: Bivariate Probit Estimates with Alternative Matching

Variables	Full Sample		Girls		Boys	
	(1)	(2)	(3)	(4)	(5)	(6)
	Work	School	Work	School	Work	School
Post	1.204***	-0.854***	1.327***	-0.698*	1.389***	-0.899***
	(0.314)	(0.256)	(0.479)	(0.358)	(0.466)	(0.332)
Raskin	0.404*	-0.187	0.208	-0.115	0.666**	-0.285*
	(0.227)	(0.116)	(0.370)	(0.159)	(0.295)	(0.168)
Raskin*Post	-0.486*	0.061	-0.354	0.173	-0.760**	-0.216
	(0.258)	(0.163)	(0.405)	(0.225)	(0.346)	(0.236)
Child characteristics						
Child gender	-0.185**	0.215**				
	(0.093)	(0.083)				
Child age	0.028	2.821***	0.160	2.832***	0.257	3.004***
	(0.188)	(0.134)	(0.222)	(0.207)	(0.246)	(0.164)
Child age2	0.011	-0.137***	0.002	-0.137***	0.005	-0.146***
	(0.009)	(0.007)	(0.011)	(0.010)	(0.012)	(0.008)
Child religion Islam	-0.632**	-0.130	-0.564	0.108	-0.858***	-0.111
	(0.247)	(0.215)	(0.387)	(0.272)	(0.292)	(0.270)
Household characteristics						
Urban	-0.004	0.158	0.243*	0.049	-0.201	0.323**
	(0.120)	(0.100)	(0.141)	(0.127)	(0.201)	(0.146)
Household size	0.045	-0.029	0.011	-0.023	0.095*	-0.029
	(0.035)	(0.029)	(0.049)	(0.041)	(0.051)	(0.041)
Dependency ratio	0.192**	0.010	0.225**	0.144	0.191	-0.089
	(0.080)	(0.074)	(0.112)	(0.126)	(0.121)	(0.084)
HHH female	-0.097	0.005	0.033	0.054	-0.176	-0.004
	(0.188)	(0.156)	(0.273)	(0.199)	(0.279)	(0.222)
Assets per capita (ln)	0.031	0.090**	0.049	0.074	-0.001	0.094*
	(0.045)	(0.041)	(0.065)	(0.062)	(0.068)	(0.055)
Per capita expenditure	-0.030	0.329***	-0.183	0.292**	0.179	0.354***
	(0.102)	(0.088)	(0.143)	(0.131)	(0.146)	(0.120)
Own business	0.363***	0.007	0.604***	-0.082	0.172	0.173
	(0.102)	(0.089)	(0.142)	(0.118)	(0.159)	(0.129)
Own farmland	0.354***	0.017	0.385***	-0.086	0.254	0.116
	(0.099)	(0.093)	(0.136)	(0.128)	(0.165)	(0.126)
Electricity	0.030	0.160	1.017**	0.277	-0.248	-0.017
	(0.187)	(0.176)	(0.395)	(0.251)	(0.244)	(0.209)
Water	0.062	-0.146	0.214	-0.088	-0.145	-0.276*
	(0.136)	(0.109)	(0.175)	(0.148)	(0.220)	(0.155)
Cook firewood	0.229*	0.036	0.373**	0.191	0.144	-0.132
	(0.127)	(0.113)	(0.152)	(0.165)	(0.201)	(0.153)
Toilet - river/land/sea	-0.231	0.032	-0.583**	-0.153	-0.248	0.146
	(0.146)	(0.118)	(0.258)	(0.158)	(0.195)	(0.162)
Poor sanitation	0.134	-0.061	0.268	0.056	0.064	-0.191
	(0.119)	(0.125)	(0.171)	(0.144)	(0.167)	(0.183)
Parent characteristics						
Mother age	0.024**	0.004	0.041**	-0.012	0.024	0.019
	(0.012)	(0.010)	(0.018)	(0.015)	(0.016)	(0.014)
Father age	-0.016*	0.007	-0.033**	0.012	-0.013	0.004
	(0.009)	(0.009)	(0.014)	(0.015)	(0.013)	(0.012)
Mother married	-0.028	-0.027	-0.748*	-0.271	0.554	0.114
	(0.311)	(0.278)	(0.399)	(0.410)	(0.579)	(0.329)
Mother paid occupation	0.089	-0.056	0.115	0.039	-0.058	-0.171
	(0.107)	(0.092)	(0.149)	(0.128)	(0.154)	(0.124)
Father paid occupation	-0.014	-0.025	0.047	0.037	0.281	-0.125
	(0.179)	(0.146)	(0.259)	(0.229)	(0.278)	(0.178)

Mother - elementary	-0.248	0.477***	-0.482*	0.453**	-0.232	0.429**
	(0.177)	(0.153)	(0.266)	(0.219)	(0.257)	(0.218)
Mother-junior	-0.492**	0.693***	-1.049***	0.508	-0.045	0.822***
	(0.243)	(0.217)	(0.338)	(0.328)	(0.376)	(0.294)
Mother - senior	-0.249	0.619***	-1.079***	0.807**	0.058	0.426
	(0.308)	(0.227)	(0.394)	(0.347)	(0.469)	(0.291)
Mother - tertiary	-0.439	0.992***	-1.152**	1.014***	-0.206	0.883*
	(0.407)	(0.308)	(0.551)	(0.393)	(0.721)	(0.460)
Father - elementary	-0.025	0.079	-0.206	0.159	0.057	0.075
	(0.198)	(0.175)	(0.319)	(0.228)	(0.280)	(0.210)
Father - junior	0.025	0.331	-0.050	0.429	0.008	0.295
	(0.228)	(0.207)	(0.370)	(0.290)	(0.336)	(0.253)
Father - senior	-0.394	0.115	-0.135	0.046	-0.872*	0.266
	(0.305)	(0.207)	(0.427)	(0.286)	(0.445)	(0.270)
Father-tertiary	-0.679	-0.213	0.064	0.017	-6.711***	-0.214
	(0.423)	(0.263)	(0.537)	(0.356)	(0.673)	(0.339)
Mother - highest edu	0.248*	0.041	0.229	0.049	0.455**	-0.010
	(0.138)	(0.100)	(0.209)	(0.142)	(0.181)	(0.139)
Father - highest edu	-0.140	0.071	-0.118	0.017	-0.277	0.110
	(0.128)	(0.102)	(0.172)	(0.130)	(0.186)	(0.148)
Constant	-3.938**	-18.115***	-11.059***	-15.689***	-6.743***	-20.755***
	(1.815)	(1.703)	(2.834)	(2.909)	(2.544)	(1.931)
Rho	-0.403***		-0.368**		-0.582***	
	(0.083)		(0.144)		(0.132)	
Observations	3,532	3,532	1,805	1,805	1,727	1,727

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels All estimations include household, year and province fixed effects as well as the corresponding weights generated by CEM.

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Chapter 5

Conclusion

We openly talk about the importance of mental health in today's society, particularly as poor mental health among children and adolescents is on the rise. However, has it ever been in connection with harmful practices such as child labour and child marriage that still exist mostly in developing countries? This thesis primarily aimed to shed light on this broad question by drawing longitudinal household-level data from Indonesia.

The second chapter examines the impact of early marriage on the mental health of women. The study finds that women who marry early are more likely to be affected by depression as well as severe depressive symptoms. Additionally, this study shows that a one-year delay in marriage decreases the probability of having severe depression. This corresponds with the original estimates, given that an early marriage is likely to increase the probability of having depression.

The third chapter investigates the long-term effect of child labour on adolescent mental health. The results reveal that child labour has a substantial negative impact on a child's long-term mental health status. Furthermore, the study finds heterogeneity in the effect of child labour, where working as a child for wages leads to depression seven years later. On the contrary, there is no significant impact of working as a child in family enterprises on adolescent mental health. This study also identifies religiosity and social capital as potential mediating factors that could subdue the adverse long-term effects of child labour on mental health.

In contrast to the previous two studies, the fourth chapter evaluates the impact of a food subsidy program (known as Raskin) on child labour and schooling of children in

Indonesia. The results suggest that the subsidised rice program is effective in decreasing the probability of working for boys though there is no impact on the outcomes of girls. Specifically, it is found that the Raskin program significantly reduces the likelihood of working for boys who engage in both working and schooling.

It is important to highlight several limitations of the thesis. First, the use of self-reported data on key variables such as mental health, child labour can cause measurement error leading to biased estimates. However, to validate these self-reported data, we use national statistics and show that there are no significant differences. Second, our analysis is limited in scope such that we primarily focus on the effect of childhood adversity on mental health. Therefore there is no empirical analysis of potential mechanisms that might explain the observed effect. This limitation is mainly due to the availability of data. An area for future research would be to explore these mechanisms, especially in developing countries, so as to provide better insights for policy implications.

In conclusion, the overall findings of the thesis highlight the need to accelerate the progress towards eliminating harmful practices such as child labour and child marriage as the consequences of it affect not only the physical wellbeing but also the emotional wellbeing of children. Moreover, it suggests that pro-poor programs such as subsidised food programs are a potential policy response in addressing issues such as child labour. Taken together, the thesis provides key implications on why and how we should promote child wellbeing and thereby better outcomes for children.