Idiosyncratic Shocks, Well-being and Labour Market Outcomes in Sub-Saharan Africa

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Idiosyncratic Shocks, Well-being and Labour Market Outcomes in Sub-Saharan Africa

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Declaration

I, **Gidisa Lachisa Tato**, hereby declare that the work presented in the thesis, titled "Essays on Idiosyncratic Shocks, Well-being, and Labour Market Outcomes in Sub-Saharan Africa," submitted to Addis Ababa University, Ethiopia, in partial fulfillment of the requirement for the award of the degree of Doctor of Philosophy in Economics, is an original piece of research work. I confirm that all sources of materials utilized in this thesis have been properly cited.

I declare that I conducted the research on my own initiative, with the advice and support of my supervisors, Yonas Alem (PhD), University of Gothenburg, Sweden, and Assefa Admassie (PhD), Addis Ababa University, Ethiopia. I have not submitted the material contained in this thesis for the award of any other degree or professional qualification.

The material presented in Chapter Two was previously published in *World Development*, which I co-authored with my PhD supervisor, Yonas Alem. Similarly, the work described in Chapter Three is co-authored with my other supervisor, Assefa Admassie (PhD), which is submitted for publication and it is under review.

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This is to certify that the dissertation prepared by ***Gidisa Lachisa Tato Idiosyncratic Shocks, Well-being and Labour Market Outcomes in Sub-Saharan Africa*** and submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Economics complies with the regulations of the university and meets the accepted standards with respect to originality and quality.

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Dedication

I dedicate my dissertation work to my lovely wife Mignot**e**, my son Keanan, and my two daughters Nafilet and Milki. You have made me stronger, better and more fulfilled than I could have ever imagined. This work is also dedicated to my loving parents, Lechu (Lachisa) and Taye (Tayitu) whose words of encouragement and good examples have taught me to work hard for the things that I aspire to achieve.

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Acronyms and Abbreviations

AAU	Addis Ababa University
ATT	Average Treatment Effect
BMI	Body Mass Index
CES-D	Center for Epidemiological Studies Depression Scale
CRE	Correlated Random Effects
CSA	Central Statistical Agency
CSMs	Continuing Sample Members
DID	Difference-in-Differences
EfD	Environment for Development
EPWP	Expanded Public Works Programme
ERHS	Ethiopian Rural Household Survey
FE	Fixed Effects
HRS	Health and Retirement Survey
ILO	International Labour Organization
NIDS	National Income Dynamic Study
OLS	Ordinary Least Squares
PSM	Propensity Score Matching
SALDRU	Southern African Labour and Development Research Unit
SDGs	Sustainable Development Goals
Sida	Swedish International Development Cooperation Agency
SNNP	Southern Nations, Nationalities and Peoples
SSA	Sub-Saharan Africa
SWB	Subjective Well-being
TSMs	Temporary Sample Members
TWFE	Two-way Fixed Effects
UK	United Kingdom
UNICEF	United Nations International Children's Emergency Fund
US	United States
WHO	World Health Organization

Chapter One

Introduction

1.1. Background

Many households in less developed nations face significant vulnerabilities stemming from various unexpected events, which can have both immediate and lasting consequences. These events typically fall into two categories: idiosyncratic and covariate shocks. Idiosyncratic shocks, such as individual or small-scale incidents like death, illness, job loss, or asset damage, impact specific households. In contrast, covariate shocks, like droughts, conflicts, inflation spikes, or widespread floods, affect multiple households within the same region. Weather-related disasters, fluctuations in agricultural commodity prices, famine, and armed conflicts are among the most prevalent covariate shocks experienced by households in developing countries (Adhvaryu et al., 2019; Singhal, 2019; Abiona, 2017; Dercon and Porter, 2014; Ampaabeng and Tan, 2013; Maccini and Yang, 2009). Health-related crises such as illness and mortality, along with unemployment shocks, are also common idiosyncratic shocks in these regions (Bratti and Mendola, 2014; Alam, 2015; Andersen, 2013; Maccini and Yang, 2009; Gay and Tonge, 1967; Harris et al., 1986, 1990).

The victims' livelihoods suffer as a result of their exposure to such shocks. Evidence suggests that the livelihood systems of victims harmed by these shocks are degraded, trapping them in poverty for generations (Lindo, 2011; Andersen, 2013; Bratti and Mendola, 2014; Alam, 2015). Studies show the effect of idiosyncratic and covariate shocks on socioeconomic indicators of household welfare. There is evidence that illness and disability of a household member (Asfaw and Braun, 2004; Beegle et al., 2008; Cochrane, 1991; Dercon and Krishnan, 2000; Gertler and Gruber, 2002; Lindelow and Wagstaff, 2006; Wagstaff, 2007), drought (Dercon, 2004; Dercon et al., 2005; Maccini and Yang, 2009; Abiona, 2017; Adhvaryu et al., 2018), food price inflation (Ivanic and Martin, 2008; Tiwari and Zaman, 2010; Alem and Söderbom, 2012), armed conflict and violence (Adong et al., 2021; Alloush and Bloem, 2022; Bertoni et al., 2019), and parental unemployment (Andersen, 2013) significantly affect household welfare through reduced education, labour market participation, income, and poor health outcomes.

One of the key contrasts in the analysis of the impact of idiosyncratic shocks vs. covariate shocks on socioeconomic outcomes relates to potential mitigation measures, such as the availability and viability of insurance arrangements against such shocks. The impact of idiosyncratic and covariate shocks can be fully or partially reduced in contexts where insurance and credit markets are available. However, in situations where insurance and credit markets do not properly function, idiosyncratic shocks are frequently partially covered through informal risk-sharing and consumption smoothing mechanisms. Covariate shocks, on the other hand, are less insured (Bardhan and Udry, 1999).

One of the key reasons that covariate and idiosyncratic shocks have a long-term impact in developing nations is a lack of formal insurance mechanisms against such shocks in these countries (Jung and Tran, 2012; Robinson, 2012; Mobarak and Rosenzweig, 2013; Jensen and Barrett, 2017). However, the significance of informal insurance in mitigating the impact of idiosyncratic shocks in developing countries is acknowledged in the literature (Dercon, 2005; Heltberg and Lund, 2009; Robinson, 2012; Abrokwah et al., 2019). The role of extended families and social networks has also been shown to reverse the potentially negative effects of idiosyncratic shocks on the livelihood of victims (Case et al., 2004; Kazeem and Jensen, 2017; Novella, 2018; Beegle et al., 2010; De Vreyer and Nilsson, 2019; Ardington and Leibbrandt, 2010; Parker and Short, 2009). Given these two perspectives, the influence of idiosyncratic shocks on the welfare of people, particularly in developing countries such as those in Africa, is unclear. This dissertation therefore explores the effect of idiosyncratic shocks on the most common socio-economic outcomes, such as those related to mental health, and labour markets, including child labour outcomes. The thesis investigates the effect of idiosyncratic shocks on mental health and labour market outcomes using rich household panel data from South Africa, while it studies the impact of similar shocks on child labour using data spanning over a decade from Ethiopia.

Mental health disorders rank among the primary contributors to the global disease burden. Depression, anxiety, schizophrenia, and bipolar disorder stand out as the most prevalent mental health challenges worldwide, with depression notably leading as a significant cause of years lived with disability (Foundation, 2016). According to Collins et al. (2013), mental health illnesses account for roughly one-quarter of all years lived with disability. Recent evidence consistently reveals that mental health disorders account for 21.2% of years lived with disability.

There is evidence to show that mental health disorders affect 35-50% of the population in developed countries and 76-85% of the population in developing countries (Foundation, 2016). Thus, mental health illnesses constitute a significant hurdle for inhabitants of developing countries.

A mental health illness or disorder is a condition that alters how a person feels, and thinks about others, and how they behave, and interact with others. Mental disorders include a wide spectrum of mental and behavioral problems, including depression, anxiety, schizophrenia, intellectual disability, and drug abuse disorders (WHO, 2017). If such diseases progress, they render people's daily activities unproductive, both socially and economically. According to WHO (2013), the most prevalent effects of mental illness include disproportionately higher rates of disability and mortality among those affected. Furthermore, it contributes to rising poverty, suicide rates, and poor healing from other ailments.

In traditional conceptions of well-being, as stated by Seow et al. (2016), the two fundamental aspects of mental health are hedonic and eudaimonic well-being. Hedonic well-being, which is the emotional aspect, involves how people deal with happiness, satisfaction, and interest in life. Hedonic well-being is assessed by the presence of emotional experiences such as joy, fascination, anxiety, sadness, anger, and affection (Kahneman and Deaton, 2010). According to Galderisi et al. (2015), emotional wellbeing (related to happiness) is one of the components of mental health identified by Keyes (2005), in addition to psychological well-being (related to self-realization) and social well-being (related to social relations). According to Feller et al. (2018), emotional well-being includes physiological well-being, positive mental well-being, health-related quality of life, life prosperity, and life satisfaction. This dissertation therefore employs emotional well-being disorder to describe mental health disorders. Depression, the topic of a part of this dissertation, is the leading cause of disability worldwide, impacting 264 million people. Nearly 80% of people suffering from depression in low- and middle-income countries do not obtain treatment (WHO, 2020).

Other key outcomes of interest in developing countries are labour market outcomes such as those related to employment and earnings. The labour market in developing countries, particularly in low-income countries, is characterized by low labour demand due to stagnant growth and an unprecedented supply of labour fueled by population growth. High levels of unemployment and underemployment, as well as high employment in informal sectors in urban areas and agriculture in rural areas, are among the distinctive features of developing-country labour markets (Frölich & Haile, 2011). Fields (2011) recognizes that countries with emerging economies have lower rates of unemployment than developed countries but relatively low earnings and unpredictable incomes. A rapidly expanding working-age population in developing countries is predicted to increase labour market pressure. Over 1 billion people are predicted to be added to the working-age population globally between 2020 and 2050, with SSA accounting for roughly 70% (Lam & Elsayed, 2021).

The youth are the most vulnerable to unfavorable labour market outcomes in this rapidly rising working-age population. For example, the global youth unemployment rate is 15.2%, which is three times higher than the adult unemployment rate. In Africa, where youth make up more than 22% of the labour force, the youth unemployment rate is 12.5% (ILO, 2022). High youth unemployment on the continent is exacerbated by work in non-standard, informal, and precarious occupations, causing the young to live in poverty. More than 95% of employed youths in Sub-Saharan Africa (SSA) work in informal occupations with minimal income stability and no social security coverage. As a result, around 42% of the continent's young workers were living in extreme poverty in 2019, with the remaining 27.2% living in moderate poverty (ILO, 2020).

Recognizing the aforementioned labour market challenges in developing nations, there is a need to build realistic, research-based policies because is the primary asset for the poor and the primary source of income for households. In low- and middle-income countries, for example, labour income accounts for more than half of total household income (Fields, 2012; van Treeck, 2020). Fields (2012) thus underlines the importance of understanding labour markets and labour earnings in developing countries to understand global poverty. This dissertation therefore explores labour markets in relation to the effect of early-life parental death on adult employment and earnings.

In addition to negative labour market outcomes, the presence of child labour is an issue in developing countries. Although there is no agreement on the definition of child labour, conventional indicators show that child labour is common in poor nations. According to UNICEF's standard indicator, a child is considered a labourer if the child is 1) age 5 to 11 years and undertakes at least 1 hour of economic work or 21 hours of unpaid household services per week; 2) age 12 to 14 years and undertakes at least 14 hours of economic work or 21 hours of unpaid household services per week; 3) age 15 to 17 years and undertakes at least 43 hours of economic work per week (UNICEF, 2021). According to this definition, recent estimates reveal that 160 million children (and 39.4% of girls) were engaged in child labour globally at the start of 2020, with over half engaged in hazardous work that directly endangers their well-being. Sub-Saharan African children are the most vulnerable to child labour, accounting for more than half of the global total (ILO and UNICEF, 2021).

Child labour is prevalent in Ethiopia, as it is in other Sub-Saharan African nations. According to the 2001 Ethiopian child labour survey (CSA, 2001), 85% of children aged 5-17 were involved in some type of household work, with 52.1% engaging in economic activities. The 2015 Child Labour Survey (CSA, 2015) found that 71% of children aged 5-17 were engaged in home tasks and 51% were engaged in economic activities. In 2015, 42.7% of children in Ethiopia aged 5-17 ere engaged in child labour, according to the ILO criteria. Due to the high prevalence of child labour globally, national and international organizations are working to tackle the problem. For example, one of the United Nations Sustainable Development Goals (SDGs) is to eliminate all types of child labour by the year 2025.

This research, in general, investigates the effect of household-specific shocks on key socioeconomic outcomes in SSA. The second chapter of this dissertation investigates the relationship between household shocks such as the death of household members and property loss and the victim households' mental health. The third chapter explores the impact of biological parent loss in childhood on later-life labour market outcomes, such as employability and salary or wage income. The final chapter examines the dynamic influence of biological parent loss on child labour outcomes.

1.2. Objective of the Dissertation

The overall objective of this dissertation is to assess the effect of idiosyncratic shocks on household livelihoods in Africa.

More specifically, the dissertation aims to:

- Analyze the contemporaneous effects of household idiosyncratic shocks on mental health in Africa, using panel data from South Africa.
- Assess the long-term effect of early-life shocks on employment and earnings during adulthood in Africa, drawing on panel data from South Africa.

- Investigate the dynamic (short- and long-term) impacts of household shocks (parental death) on child labour in Africa, using data from Ethiopia.

1.3. Contributions of the Dissertation

The research in this dissertation will contribute to the development economics literature and specifically to the literature on shocks, mental health, the labour market, and child labour in Sub-Saharan Africa. The focus on the impact of specific types of idiosyncratic shocks, which has received little attention in the literature, is one of the dissertation's primary contributions. Despite the growing relevance of the problem worldwide, particularly in developing nations, there is little robust empirical research in the literature on shocks and mental health, and on the impact of idiosyncratic shocks on mental health. Most studies consider early life covariate shocks (Adhvaryu et al., 2019; Singhal, 2019), economic insecurity (Rohde et al., 2016; Watson and Osberg, 2017), exogenous income shocks in the form of cash transfers or lottery winnings (Apouey and Clark, 2015; Haushofer and Shapiro, 2016), or precarious employment (Caplan et al., 1989; Fiori et al., 2016; Moscone et al., 2016) to study their effect on mental health problems. The idiosyncratic shock of the death of parents or household members is distinct in that it is permanent with possible long-term effects on children, unlike other types of idiosyncratic or covariate shocks.

Little is known about the effect of non-economic and idiosyncratic shocks on mental health disorders. Lindeboom et al. (2002) evaluated the influence of a partner's or a close person's death or sickness on the mental health of older people and discovered a statistically significant association. Siinger (2017) discovered a long-term effect of a spouse's death on the surviving partner's mental health state when she examined data from elderly people. The second chapter of this dissertation expands on the literature in two ways. First, it considers the death of any member of the household rather than only a spouse or a close relative. Property loss due to events such as livestock disease or death, crop failure, theft, or fire is evaluated, which has received little attention in the literature. Third, emphasis is placed on recent negative life experiences, as recent shocks have a greater impact than earlier shocks (Watson and Osberg, 2017).

Previous research on early life shocks and late life outcomes focused on covariate shocks that were linked to intermediate outcomes such as those related to education and health. There is little evidence on how early life idiosyncratic shock on parents affects their children's later life results, with most of the research concentrating on non-labour market outcomes. For example, studies have demonstrated a negative effect of parental loss in childhood on later-life psychiatric disorders (Gay and Tonge, 1967; Harris et al., 1986, 1990). Beegle et al. (2010) reveal that orphanhood has a negative impact on long-term health and educational outcomes. Most other research looked at the immediate impact of parental shock on children's outcomes. For example, parental unemployment has been shown to have an impact on children's educational performance (Andersen, 2013). Other research has consistently indicated that parental health shocks have a negative impact on children's education (Bratti and Mendola, 2014; Alam, 2015).

The third chapter of this thesis adds to the literature by looking at idiosyncratic shocks and how they relate to labour market outcomes. Limited academic research has been conducted to investigate the impact of early-life idiosyncratic shocks on labour market outcomes, particularly in developing countries. There is substantial evidence that households in developing nations are frequently hit by idiosyncratic shocks like illness, death, loss of property, and unemployment, which have a negative impact on the victims' and/or subsequent generations lives. According to Börner et al. (2015), idiosyncratic shocks such as illness and the death of a household member are connected with labour reallocation and asset depletion. Heltberg and Lund (2009) established idiosyncratic shock as the most common shock in Pakistan and demonstrated its negative impact on food security, debt, and child labour. According to Günther and Harttgen (2009), idiosyncratic shocks have a greater impact on the vulnerability of urban households. Beegle et al. (2010) have demonstrated how the deaths of parents affect future generations' human capital. This chapter thus analyzes the impact of early-life parental loss on late-life labour market outcomes.

The literature on the relationship between parental mortality and child labour is also limited, although there are studies that link parental death to child health and education outcomes. There is also empirical research that links parental infirmity or illness to child labour. Amato and Anthony (2014) discovered a decline in children's well-being (measured by markers linked with knowledge, skills, and behavioral concerns) following parental death by employing a child fixed effect to draw causation from parental death to child outcomes. Using the same methodology, Cas et al. (2014) discovered that parental mortality has a detrimental influence on children's educational performance, with a greater impact of a father’s death and for older children. According to Gimenez et al. (2013), parental mortality has a long-term effect on human capital accumulation because victim children are more likely to substitute income-earning jobs for higher education.

Edmonds (2010) discovered a positive correlation between father incapacity and the worst types of child labour in the literature on idiosyncratic household shock and child labour. Similarly, parental illness has been shown to reduce educational results (attainment, enrollment, or attendance) and increase child labour (Lim, 2020; Mendolia et al., 2019; Woode, 2017). Woode (2017) demonstrated the importance of health insurance in mitigating the negative effects of such shocks. Dinku et al. (2018) investigated the influence of parental health shocks (sickness) on child time allocation in Ethiopia. They discovered that parental illness increases children's time allocation on income-generating and domestic tasks, with noticeable variability across gender, using a fixed-effects Poisson model. Kamei (2018) used a sequential logit model to investigate the influence of parental absence (the death of the father) on children's participation in hazardous labour. The study showed that the absence of a father due to death increases the chance of children engaging in hazardous labour.

Given the importance of parents in their children's time allocation, it is worthwhile to investigate the influence of their absence. Parental absence may have an impact on child labour through economic shocks and/or a lack of investment incentives by a non-biological parent or victim child caregiver (Edmonds, 2007). The study in Chapter 4 adds to the literature by investigating the short- and long-term dynamic impact of parental mortality on child labour, which is not well addressed in the literature. This chapter also contributes to the empirical literature by developing causal interpretations of child labour factors using strong identification methodologies.

1.4. Data

This dissertation's empirical study makes use of panel datasets from South Africa and Ethiopia. The research in chapter two and three are based on data from the National Income Dynamics Study (NIDS), conducted in South Africa. The study in chapter four is based on data from the Ethiopian Young Lives survey.

The NIDS data are from a national panel survey conducted in 2008, 2010-2011, 2012, 2014-2015, and 2017. The survey was sponsored by the South African government's Department of Planning, Monitoring, and Evaluation and was undertaken by the Southern African Labour and Development Research Unit (SALDRU) in the University of Cape Town's School of Economics. It tracks roughly 28,000 people in 7,305 South African households during the first wave, in 2008. The survey's goal is to uncover the dynamic structure of households as well as changes in households' living situations and well-being. Continuing Sample Members (CSMs) were household members in wave one and offspring born to female members in the following waves. Co-residents with the CSM during the interviews, known as Temporary Sample Members (TSMs), were included in the survey (Brophy et al., 2018).

Based on individual-level and household-level questionnaires, the data document changes in poverty and well-being; household composition and structure; fertility and mortality; migration, labour market participation, and economic activity; human capital formation, health, education; amongst other topics. The NIDS data is one of the most complete and rich datasets on the African continent, documenting precise socioeconomic data for the same individuals over time. The attrition rate in the sample is estimated to be about 18%, with high-income earners dropping out more from the survey more frequently (Hundenborn et al., 2019). 73% of those interviewed in wave 1 were successfully interviewed in wave 5. With further lower attrition, 77%, 87%, and 92% of the individuals added as CSMs in the subsequent three waves, respectively, were successfully interviewed in wave 5 (Brophy et al., 2018). For the purpose of the analysis, data on all adult respondents in the CSMs observed in at least two rounds and with complete information are used. This is due to the use of panel data estimators, most notably the fixed effects and correlated random effects estimators, which require at least two rounds of data for each individual to identify the parameters of interest.

To explore the link between parental death and child labour, the study uses five rounds (2002-2016) of panel data from the Young Lives survey, an International Study of Childhood Poverty in Ethiopia, obtained from UK Data Service. During the first survey round in 2002, 2000 one-year old children (hereafter `younger' cohort) and 1000 eight-year-old children (hereafter `older' cohort) were enumerated. The same children were tracked in the follow-up survey rounds (round 2 in 2006, round 3 in 2009, round 4 in 2013, and round 5 in 2016). The samples were drawn from children located in 20 sentinel sites found in four main regional states and the capital city of the country, those of Amhara, Oromia, Southern Nations, Nationalities and Peoples (SNNP), Tigray, and Addis Ababa city administration. These regions represent 96% of the national population. However, the sample sentinel sites were selected purposefully and the sample deemed to represent a certain type of population. The aggregate attrition rate, including dropouts due to death from rounds 1 to 5, is limited to 9.6% (4.3% due to death) for the younger cohort and 18.8% (1.1% due to death) for the older cohort (Young Lives, 2017).

1.5. Methods of Analysis

Panel data estimation strategies are adopted to explore the link between idiosyncratic shocks and the socio-economic outcomes considered in this dissertation. The specific panel data estimation used, however, depends on the specific question raised and addressed in each chapter of this dissertation. Both descriptive and inferential analyses are adopted. The descriptive analysis is presented using tables and graphs. While the detailed estimation approaches for inferential analysis are presented under coverage of each chapter, this section provides a summary of the approaches used.

Chapter two analyzes the link between shocks and mental health. The shock factors under consideration are the deaths of household members and the loss of property at a given time *t*. These variables are dummies, with a value of one if the household received the shocks during the survey round and a value of zero otherwise. The outcome variable (mental health) is assessed using the Center for Epidemiological Studies Depression Scale (CES-D 10). The CES-D scale responses for the 10 scale items range from 0 (rarely or never) to 3 (most or all of the time), with total scores ranging from 0 to 30. Depression is also measured on an ordinal scale to assess mental wellness. The fixed effects estimator is the key empirical strategy with the aforementioned information and other controls. For robustness testing, various methodologies such as correlated random effects, random effects ordered Probit, and fixed effects Poisson estimators are used.

The third chapter includes findings on the impact of early-life shocks on adult labour market outcomes. Wage earnings and work status during adulthood are documented in the survey rounds to capture labour market outcomes. Wage earnings are calculated in monetary terms, while employment status is captured using an unemployed dummy. The main independent variable, the death of either of the respondents' biological parents before their fifth birthday, is a time-invariant dummy variable. In this setup, estimation using a fixed effects estimator eliminates the coefficient of time-invariant independent variables. To tackle this, a Correlated

Random Effects (CRE) approach, developed by Mundlak (1978) and relaxed by Chamberlain (1980, 1982), helps to account for the fixed effect of time-varying covariates while maintaining the estimates of time-constant variables. More specifically, the approach has the advantage of estimating the effect of time-varying variables while providing effect estimates of time-invariant variables that are unbiased due to a possible correlation with time-varying unobserved heterogeneity (Wooldridge, 2013; Schunck, 2013). Therefore, CRE is used as the main estimation approach, with alternative approaches such as Heckman selection, random effects probit, and Hausman-Taylor estimators used for robustness checks.

A natural quasi-experimental technique is used to investigate the dynamic impact of parental mortality on child labour described in Chapter 4. Child labour is measured using the total daily hours that a child spends on economic and non-economic activities at home or outside of the home. The treatment variable is the death of the biological parent, and the treatment is irreversible. With the availability of four rounds of panel data, the natural treatment can happen in any of the subsequent three rounds among the treated groups, with the first round serving as the base year. Given the nature of the treatment, a staggered Difference-in-Differences (DID) approach described by Callaway and Sant'Anna (2021) is utilized in this study to capture the dynamic causal effect of parental death on child labour. This method particularly compensates for: a) multiple time periods; b) variations in treatment timing; and c) the parallel trend assumption holding after conditioning on observed covariates.

1.6. Summary of Findings

The estimation results presented in this dissertation, based on evidences from developing countries, show a statistically significant relationship between idiosyncratic shocks and the socioeconomic outcomes investigated, with evidence drawn from developing countries. The following are the specific findings:

- Idiosyncratic shocks, and especially the death of a family member, are highly related to poor mental health outcomes. The magnitude nearly doubles when death occurs unexpectedly, such as in an accident or due to violence, and increases by 35% when the deceased is a close family member of the respondent. Bereavement and income loss are two probable processes that could explain the connection between the death of a household member and poor mental health.

- Early loss of biological parents is related to a lower likelihood of being employed and receiving salary earnings. The association is stronger with the loss of a biological mother than a biological father. The loss of a biological mother is substantially connected with poorer outcomes related to education levels, perceived health, cognitive ability, and occupation type, but only poorer education outcomes are associated with the loss of a father. These factors are plausible mechanisms that could explain the link between the early life loss of biological parents and labour market outcomes.
- A quasi-experimental analysis using a conditional staggered difference-in-difference estimator also reveals a statistically significant impact of parental death on increasing child labour in Ethiopia. Alternative estimations also reveal four key results. First, the cumulative effect of parental death is stronger than the immediate effect. Second, the impact of parental death is greater at around 12 years old than at earlier or later ages. Third, the death of a parent forces children to perform unpaid household services rather than to engage in economic activities. Finally, the death of a mother has a greater impact on child labour outcomes than the death of a father.

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Chapter Two

Shocks and Mental Health: Panel Data Evidence from South Africa[1]

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Abstract

Households in developing countries are subject to considerable risk and shocks, but most can't deal with them using formal credit and insurance mechanisms. We use five rounds of the South African NIDS panel data and investigate the links between shocks and mental health as measured by the Center for Epidemiological Studies – Depression Scale (CES-D). We find that experiencing idiosyncratic shocks, more importantly, the death of a family member is significantly associated with poor mental health. The magnitude increases by almost two-fold when death happens unexpectedly, i.e., due to an accident or violence, and increases by 35% when the deceased is a close family member of the respondent. We argue that two plausible mechanisms could explain the links between the death of a household member and mental health – bereavement and loss of income. Our results offer suggestive evidence of the large scope for improving welfare further through social support and insurance mechanisms. The results also imply the importance of expanding psychiatric and therapeutic care in Africa, which currently appears to be at the lowest level compared to the rest of the world.

JEL: I12, I15, O15

Keywords: Mental Health; CES-D Score; Shocks; Panel Data

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1. Introduction

Households in developing countries are vulnerable to considerable shocks or adverse events that may have long-term consequences. Important previous research demonstrates that idiosyncratic, and covariate shocks have negative (and often long-term) consequences.[2] For example, illness and disability of a household member (Asfaw and Braun, 2004; Beegle et al., 2008; Cochrane, 1991; Dercon and Krishnan, 2000; Gertler and Gruber, 2002; Lindelow and Wagstaff, 2006; Wagstaff, 2007), drought (Dercon, 2004; Dercon et al., 2005; Abebe and Alem, 2021), food price inflation (Ivanic and Martin, 2008; Tiwari and Zaman, 2010; Alem and Söderbom, 2012), and armed conflict and violence (Adong et al., 2021; Alloush and Bloem, 2022; Bertoni et al., 2019) significantly affect household welfare through reduced education, labour market participation and income. Early life covariate shocks also have long-term negative impacts on labour market status (Alderman et al., 2006; Manccini and Yang, 2009), education (Carrillo, 2020), and mental health (Adhvaryu et al., 2019; Singhal, 2019; Carrillo, 2020).

In this paper, we investigate the relationship between idiosyncratic shocks and mental health, an important outcome variable that has not received sufficient attention in previous studies. We draw on five rounds of the South African National Income Dynamics Survey (NIDS) to investigate the links between idiosyncratic shocks and the mental health of adults, as measured by a variant of the Center for Epidemiological Studies – Depression Scale (CES-D). The CES-D scale is a 20-item self-reported measure of depressive symptoms proposed by Radloff (1977) and widely used by researchers and mental health professionals. Using alternative panel data regressions, we show that the death of a household member and the loss of assets – two widely occurring idiosyncratic shocks that households in the sample experienced – are significantly correlated with mental health. Experiencing the death of a household member is associated strongly positively with the CES-D score of the respondent. When we decompose the death of a household member by cause of death, the parameter estimate of the death of a household member through an accident or violence is almost two times larger than the coefficient of experiencing the death of a household member. Decomposing the link by the relationship to the

[2] Idiosyncratic shocks (e.g., death, illness, loss of job, destruction of assets, etc.) are adverse events that affect one or a few households, whereas covariate shocks (e.g., drought, armed conflict, inflation, flooding, etc.) are adverse events that affect many households in the same geographical area. In set-ups where there is insurance and credit market failure, idiosyncratic shocks are often assumed to be partially insured through informal risk-sharing and consumption smoothing mechanisms. In contrast, covariate shocks are not insured (Bardhan and Udry, 1999).

respondent shows that the coefficient of experiencing the death of a close household member (daughter/son, parent, or spouse) is 25% larger than the coefficient of experiencing the death of another household member. Panel ordered probit regression results also suggest that experiencing property loss is associated with a statistically significant effect on the likelihood of feeling depressed.

This paper contributes to the rapidly evolving interdisciplinary literature on mental health in developing countries. Mental health disorders, such as depression, anxiety, schizophrenia and bipolar disorder (listed in order of importance) are major causes of the overall disease burden globally, accounting for 21.2% of years lived with a disability and costing the global economy USD 1.15 trillion each year (Chisholm et al., 2016; Foundation, 2016). Depression, the disorder we focus on in this paper, is the leading cause of disability worldwide, affecting 264 million people. Among those who suffer from it in low-and middle-income countries, close to 80% receive no treatment (WHO, 2020). While a relatively sizable number of studies have been conducted on the correlates and determinants of the mental health status of individuals in high-income countries,[3] very little research has been conducted in middle and low-income countries, especially in Africa.

In economics, Adhvaryu et al. (2019) investigates the impact of early life financial shocks on adult mental health in Ghana; Singhal (2019) studies the long-term mental health effects of the US bombing of Vietnam; Alloush and Bloem (2022) study the relationship between neighborhood violence and psychological wellbeing in South Africa, and Trinh (2020) investigates the impact of participation in child labour on the mental health of children in India and Vietnam. Studies also show that social protection improves mental health. Tsaneva and Balakrishnan (2019) find that women in the districts of the recipients of the National Rural Employment Guarantee Scheme in India were less likely to suffer from depression. Eyal and Burns (2019) use the exogenous variation in the roll-out pattern of South African child support and identify a considerable reduction in the intergenerational transmission of depressive symptoms in adolescent children.

[3] To mention a few; the economics literature identifies both idiosyncratic and covariate shocks, such as, unemployment (Green, 2011; Marcus, 2013), weight gain (Willage, 2018), high temperature (Mullins and White, 2019), economic downturn and the associated decline in wealth (McInerney et al., 2013; Nicole Black, 2021), and terrorist attacks (Kim et al., 2016) as important determinants of mental health status in industrialized countries. Epidemiological studies based on all European population studies also point out that low educational attainment, unemployment and material disadvantage (Fryers et al., 2005) and poverty and weak social support (Lehtinen et al., 2005) are associated with poor mental health.

A rapidly evolving interdisciplinary research also investigates the correlates of mental health in developing countries.[4] This strand of literature identifies social inequalities, stressful working conditions, lower levels of education, poverty, and violence and insecurity as negatively correlated with mental health. Patel and Kleinman (2003), an early review paper, draws on 11 epidemiological studies in low and middle-income countries and identifies low levels of education as the most common variable to be positively associated with common mental health disorders. These authors also show that violence and insecurity positively relate to common mental health disorders, particularly among women. Lund et al. (2010) also conducted a systematic review of 115 epidemiological studies and showed that around 79% of the studies found a positive association between poverty and common mental disorders. Relatively recently, Madhani et al. (2015) conducted a systematic review of 12 studies and documented a strong link between participation in micro-finance activities and the mental health of South Asian women. The authors also note that the longer the duration of the involvement, the more strongly access to micro-finance is related to improved mental health. Explicitly focusing on depression, Graham et al. (2017) shows that stress and lack of rest are associated with depressive symptoms of respondents in urban China.

While most of the literature focuses on the relationship of mental health disorders with education, income, socioeconomic status, poverty, and sudden social changes, such as violence and insecurity, some research finds social capital (bonding and friendship networks) as an essential correlate of mental health disorders. Miller et al. (2006) use the Indonesian Family Life Survey and show that community-level social capital is positively associated with a range of an individual's physical and mental health. Kolade et al. (2022) document that social capital plays a significant role in providing psycho-social support for households displaced by the Boko Haram insurgency in Northeast Nigeria.

We contribute to the literature on mental health in developing countries by investigating the trends in mental health disorders and their relationship with idiosyncratic shocks using nationally representative panel data from South Africa. Exploring this relationship is important

[4] A related well-established strand of multidisciplinary literature that is strongly linked with the mental health literature worth pointing out is the subjective wellbeing (SWB) literature. Studies in this literature establish that individual wellbeing or utility cannot convincingly be measured in money-metric measures, such as income, consumption, and wealth. Wellbeing is, instead, a broad measure that encompasses all aspects of human experience. Researchers in this domain use SWB as a key measure of welfare to study the impact of shocks (De and Thamarapani, 2022; Alem and Colmer, 2021), value non-market goods (Maddison and Rehdanz, 2011; Levinson, 2012; Baylis, 2020), and evaluate the impact of policies (Dolan and Metcalfe, 2012; Stutzer, 2019).

because the mechanisms by which they affect households and the institutional setups to deal with them differ from those of covariate shocks. South Africa provides an important environment to investigate the relationship between idiosyncratic shocks and mental health. It is one of the most diverse and unequal societies, with a significant fraction of the population being vulnerable to shocks (Satatistics, 2019). South Africa is also the only African country for which long panel data on detailed mental health indicators is available for a large and nationally representative sample. Our results suggest that idiosyncratic shocks are strongly correlated with the poor mental health of adults. The findings provide suggestive evidence that the impact of shocks extends beyond economic outcomes, and the welfare impact of both formal and informal mitigation and coping mechanisms are likely larger than what previous studies documented.

The rest of the paper is organized as follows: Section II presents the data and descriptive statistics. Section III presents the empirical strategy, the corresponding regression results, and robustness checks. This section also discusses the key plausible mechanisms that could explain the links between idiosyncratic shocks and mental health. Finally, section V concludes the paper.

2. Data and Descriptive Statistics

2.1. Description of Data

We base our analysis on five rounds (waves) of the National Income Dynamics Study (NIDS), a nationwide survey collected in 2008, 2010/11, 2012, 2014/15, and 2017. The survey is initiated by the Department of Planning, Monitoring, and Evaluation of the South African government and conducted by the Southern African Labour and Development Research Unit (SALDRU) based at the School of Economics, the University of Cape Town. It follows approximately 28,000 individuals who were residents in 7,305 households in South Africa during the first round, i.e., in 2008. The survey aims to reveal the dynamic structure of households and changes in citizens' living conditions and wellbeing. The household members in wave one and children born to female members in the subsequent waves participated as Continuing Sample Members (CSMs). In addition, co-residents with the CSM at the time of the interviews, called Temporary Sample Members (TSMs), were also included in the surveys (Brophy et al., 2018). Based on individual-level and household questionnaires, the data documents information on changes in poverty and wellbeing; household composition and structure; fertility and mortality; migration, labour market participation and economic activity; human capital formation, health, education, etc. The NIDS data is one of the most comprehensive and richest data sets in the African continent that documents detailed socioeconomic data of the same individuals over a long period. The attrition rate in the sample is estimated to be about 18%, with high-income earners dropping out of the survey (Hundenborn et al., 2019). We control for household income per capita in our regressions and show in Section 3.2 that our results are robust to non-random attrition. We use data on all adult respondents in the CSMs observed in at least two rounds and with complete information. We do so because panel data estimators, most notably the fixed effects estimator, require at least two rounds of data for each individual to identify the parameters of interest.

The key outcome variable of interest is the respondents' mental health state. The NIDS data collects rich information on the emotional wellbeing of adults older than 15 years at the time of the survey using the adult versions of the questionnaires. Respondents are asked ten emotional health-related questions, eight of which are about negative feelings (e.g., "I was bothered by things that usually don't bother me", or "I felt depressed"), and 2 were about positive feelings (e.g., "I felt hopeful about the future" or "I was happy"). The respondent chooses a response from the options "rarely or none of the time = 1", "some or little of the time = 2", "occasionally or a moderate amount of time = 3", and "all the time = 4". The questions are the same as the measures of depressive symptoms proposed by the Center for Epidemiological Studies Depression Scale (CES-D 10) except in the coding of responses. The respondents' choices in the CES-D scale range from 0 (rarely or none of the time) to 3 (most or all of the time), and total scores range from 0 to 30. Therefore, the NIDS emotional health indicators are constructed to match the literature.

The CES-D, initially developed by Radloff (1977), is one of the most commonly used measures of mental health disorders. Different studies reveal that for the 10-item CES-D, the cut-off score for a major depressive disorder or high risk of depression ranges from 8 (Torres, 2012) to 15 (Björgvinsson et al., 2013). An earlier study, Andresen et al. (1994), suggested a cut-off score of 10 to indicate depressive symptoms. In a validation study of the 10-item CES-D scale, Baron et al. (2017) analyze depressive symptoms in South Africa by different race groups and propose that 12 is the appropriate cut-off point to classify a respondent in the general population as "depressed". We use 8, 10, and 12 as the cut-off points to classify respondents as showing depressive symptoms for descriptive purposes but use the CES-D score as the dependent variable to measure the impact of shocks on mental health.

The key covariates of interest are the two types of idiosyncratic shocks constructed from responses of households to related questions in the household version of the NIDS questionnaire. The household version of the survey contains a module on "Negative Events" which asks households if they experienced the death of household members, accident of theft, fire or destruction of household property, widespread death and disease of livestock, and major crop failure. These different types of shocks were asked consistently in all the waves spanning 2008-2017. From the responses to these questions, we constructed two indicators (dummy) variables for "Experiencing the death of a household member" if the household experienced the death of a member. We constructed the indicator variable "Experiencing the loss of property" if the household experienced any of the shocks related to property loss or destruction in the past 24 months because the proportion of households that experienced the individual loss or property shocks is small. It is therefore important to note that the questions related to shocks refer to the past 24 months, while the question on mental health refers to the past week.[5]

The panel data regressions we present in the next section are based on the sample of households observed in at least two rounds. It is, therefore, essential to check that the results are not driven by attrition bias. We check for attrition bias by running two types of regressions. First, we follow Wooldridge (2010) and include the lead or lag of the selection (round) variable or the number of subsequent waves observed in the data. A statistically significant coefficient on the lead or lag indicates attrition bias. Second, we estimate the main regression using a sub-sample of respondents surveyed three times and five times, respectively check if the coefficients of the main variables of interest differ significantly. Section 3.2 shows that attrition is unlikely to bias our results.

2.2. Descriptive Statistics

Table 1 presents descriptive statistics of crucial household socioeconomic characteristics and the state of mental health among adult respondents in South Africa. Panel A shows that the average age of the respondents is about 38 years, around 59% of whom are female, 32% are married, 57% are single, and 11% are widowed or separated. The average respondent has 9.43 years of schooling, and half the respondents live in urban areas. South Africa is uniquely diverse in the

[5] An important idiosyncratic shock in the context of developing countries is illness (health shock). Unfortunately, questions on health shocks were asked in the "Negative Events" module of the NIDS data only in the first three rounds. Moreover, the proportion of households who experienced it in the early rounds was around 4%. Consequently, we decided not to include it in our regression analysis.

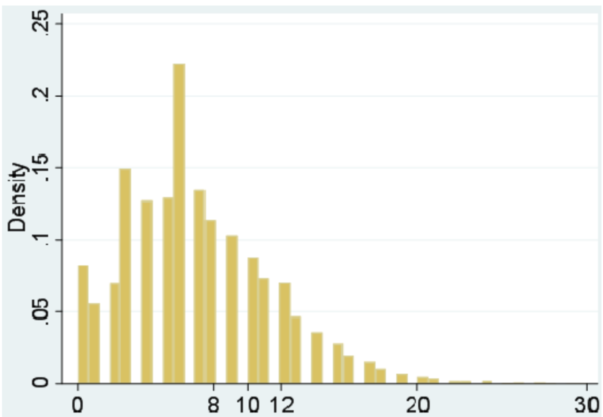
African continent in terms of the racial composition of its residents. South Africans of African origin constitute the majority (81.3%) of the respondents in the NIDS data, followed by people of mixed race or colored (14.4%), whites (3.2%), and Asians (1.2%). The most prevalent idiosyncratic shock households experience is the death of a household member, with 11% experiencing it. It is followed by the loss of property - reported by 6% of respondents.

Table 1: Descriptive statistics of variables - pooled sample

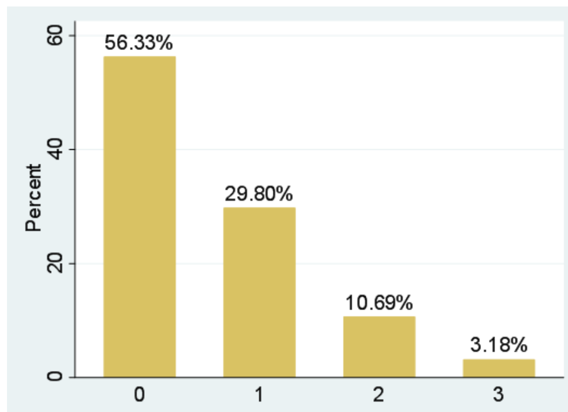
	(1) Mean	(2) SD
Panel A: Socioeconomic Characteristics		
Age	37.958	17.758
Female	0.591	0.492
Married	0.320	0.467
Widowed or separated	0.114	0.317
Single	0.565	0.496
Household income/capita (log)	6.812	1.114
Unemployed	0.146	0.353
Employed	0.372	0.483
Inactive	0.478	0.500
Years of schooling	9.427	4.230
African	0.813	0.390
Coloured	0.144	0.351
Asian/Indian	0.012	0.107
White	0.031	0.175
Urban	0.505	0.500
Experienced death of a household member	0.109	0.312
Experienced loss of property	0.062	0.242
Panel B: State of Mental Health		
CES-D score	7.024	4.396
Depressive symptom, CES-D cut-off score 8	0.392	0.488
Depressive symptom, CES-D cut-off score 10	0.257	0.437
Depressive symptom, CES-D cut-off score 12	0.156	0.363
Depressed rarely/none of the time	0.563	0.496
Depressed some of the time	0.298	0.457
Depressed occasionally	0.107	0.309
Depressed all the time	0.032	0.176
N	68102	68102

Notes: This table presents descriptive statistics (mean and SD) of key variables of adult respondents for the pooled sample.

We report mental health-related descriptive statistics in Panel B of Table 1. The average CES-D score of respondents in South Africa is about seven on a scale of 30. We compute dummy variables indicating major depressive symptoms using alternative cut-off points. Using eight as the cut-off point, about 39% of the respondents exhibit a major depressive symptom, while using ten as the cut-off point, the proportion declines to about 26%. Using 12 as the cut-off, proposed for the case of South Africa by Baron et al. (2017), we note that 16% of the respondents show a major sign of depressive disorder. When it comes to the responses to the direct question about feeling depressed, we note that those who reported feeling depressed rarely or none of the time (on less than 1 day a week) represent 56%; those feeling depressed some of the time (1-2 days a week) constitute 30%; those feeling depressed a moderate amount of the time (3-4 days) are 11%, and those feeling depressed all the time (5-7 days) are 3%. We show the distribution of CES-D scores and feeling depressed in Figure 1.



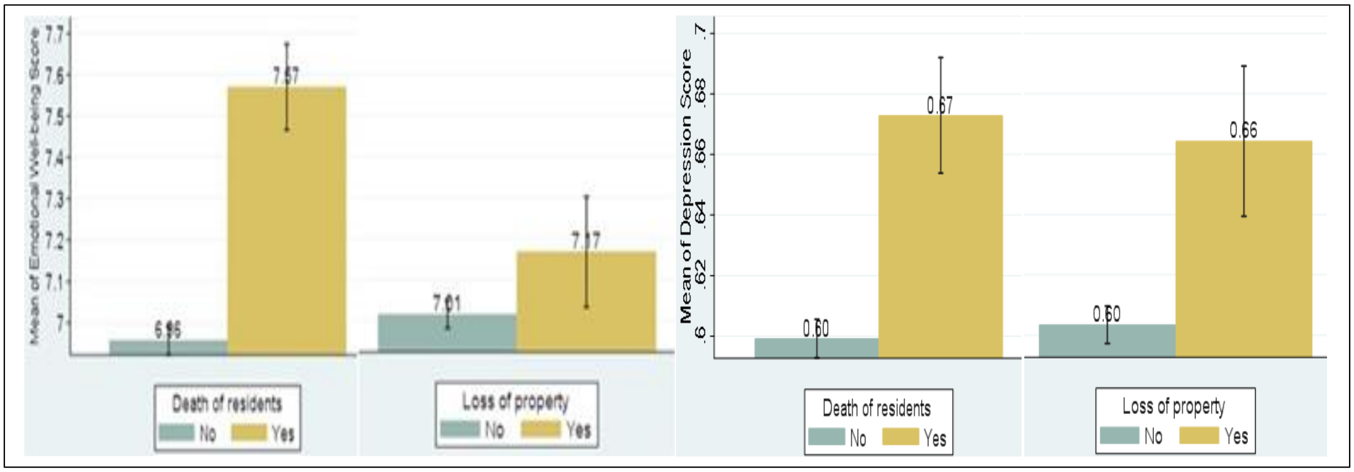
(a) CES-D Index



(b) Depression

Figure 1: Mental Health Status of Adults in South Africa

Figure 2 tests for a statistically significant difference in mental health disorders between those who experienced shocks and those who did not. Panel (a) shows a statistically significant variation in emotional well-being disorder, measured using CES-D, between those who experienced the death of a household member and those who did not. However, there is no statistically significant difference in the mental health state between the households that experienced the loss of property and those that did not. Panel (a), therefore, provides suggestive evidence for the strong correlation between the death of a household member and the mental health status of the remaining household members. Panel (b) shows a statistically significant difference in reported feelings of depression between the two groups, regardless of the type of shocks.



(a) CES-D Index

(b) Depression

Figure 2: Mental Health Status by Shocks

3. Results

3.1. Main Results

Our main aim is to explore the relationship between shocks and mental health using the South African NIDS data set. Thus, our main outcome variable of interest is an individual's mental health. We specify a linear panel data regression equation as follows:

$$M_{it} = \alpha Shocks_{it} + \beta X_{it} + \gamma Wave + c_i + u_{it} \quad (1)$$

where subscript i denotes individual, and t year. M_{it} is the mental health status of individual i at time t as measured by the CES-D score and reported feeling of depression during the week before the interview date. $Shocks_{it}$ corresponds to the vector of variables indicating whether the respondent experienced the two types of shocks (death of a household member and loss/destruction of property) by individual i during the 24 months before the interview date at time t. X represents a vector of individual and household covariates that are expected to be correlated with mental health, such as age, gender, marital status, labour market status, education of the respondent, and per capita household income. c_i corresponds to the individual fixed effect (unobserved heterogeneity), and $Wave$ represents the time-fixed effect. α, β, and γ are parameters to be estimated. The key vector of parameters of interest is α, which shows the magnitude of the correlations between shocks and an individual's mental health, estimated from a fixed effects regression. The fixed effects work through a within transformation of equation 1 to eliminate the unobserved heterogeneity term, c_i.[6] To check the robustness of our results, we also estimate the correlated random effects model (Mundlak, 1978), which allows for the correlation of the unobserved heterogeneity term c_i with the explanatory variables through controlling for the averages of the time-variant explanatory variables in equation 1. To make causal claims, both estimators require the explanatory variables of interest to be strictly exogenous. However, shocks may not be strictly exogenous because past shocks may affect current shocks and mental health. Thus, the vector of parameters α should be interpreted as correlations rather than causal estimates.

Table 2: Shocks and mental health (CES-D score): Panel data regressions

	(1) CES-D score	(2) CES-D score	(3) CES-D score	(4) CES-D score	(5) CES-D score
Death of a household member	0.325*** (0.076)		0.326*** (0.076)	0.217*** (0.076)	0.207*** (0.063)
Loss of property		-0.031 (0.161)	-0.042 (0.161)	0.042 (0.150)	0.017 (0.082)
Controls	No	No	No	Yes	Yes
Time FE	No	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Observations	68102	68102	68102	68102	68102

Notes: This table reports panel data regression results on the relationship between shocks and mental health measured by the CES-D score estimated on five rounds of the NIDS data. Columns (1) and (2) report fixed effects results controlling for the death of a household member and loss of property, respectively. Column (3) presents fixed effects results controlling for both shocks simultaneously. Column (4) reports fixed effects results controlling for shocks and other covariates of mental health. Column (5) presents results from the correlated random effects estimator controlling for shocks and other covariates. Standard errors reported in parentheses are clustered at the district council municipality level. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table 2 presents linear panel data regression results on the relationship between shocks and the mental health of adults in South Africa, estimated using five rounds of the NIDS data. Columns 1 and 2 report fixed effects regression results on the relationship between shocks and the CES-D score controlling for each shock separately. Controlling for each shock separately is essential to understand the relative importance of each shock. Column 3 reports fixed effects regression results controlling for both types of shocks. Column 4 controls for other covariates,

[6] The random effects estimator, which applies a generalized least squares estimation under the assumption of orthogonality, was also estimated. However, it was rejected by the Hausman test. Consequently, we do not report the regression results.

which previous multidisciplinary research (Patel and Kleinman, 2003; Lund et al., 2010; Green, 2011; Marcus, 2013) finds important mental health correlates. These covariates include, per capita income, years of schooling, age and its square, gender, marital status, labour market status, race, and living in urban areas. The regressions with the complete set of control variables are reported in the online appendix (Appendix A). Column 5 reports results estimated with the correlated random effects model controlling for shocks and other covariates. In all regressions, standard errors are allowed to be correlated at the district council municipal level.

The results reported in Table 2 consistently suggest that experiencing the death of a household member is strongly associated with poor mental health. Respondents who experienced the death of a household member report a 0.325 higher CES-D score (column 1) than those who did not experience the shock. Controlling for the second shock (loss of property) in column 3 doesn't change the magnitude and statistical significance of the coefficient on the death of a household member. The coefficient declines to 0.217 after controlling for other covariates of mental health and time fixed effect (column 4), but it remains statistically significant at 1%. Estimating the mental health equation using the correlated random effects estimator (column 5) doesn't change the coefficient's magnitude and statistical significance on experiencing a household member's death. Given the average CES-D score in the sample is 7.02 (Table 1), the results imply that respondents who experienced the death of a household member report about 3.1% lower mental health score than those who did not experience the shock. However, in all linear specifications, property loss does not seem to be associated with mental health at conventional significance levels.

We take advantage of the four-scale ordinal nature of the responses to the question on feeling depressed and estimate fixed effects and correlated random effects specifications for mental health. The results are reported in Table 3. Columns 1 and 2 present fixed effects results controlling for individual shocks only. Columns 3 and 4 control for both shocks and other covariates of mental health, respectively. The magnitudes and significance of both types of shocks remain fairly consistent in all specifications. An important additional result is that property loss is associated with poor mental health, controlling for individual fixed effects and other covariates. The regression results containing the complete covariates are reported in the online appendix (Appendix A).

Table 3: Shocks and mental health (Depression): Panel data regressions

	(1) Depressed	(2) Depressed	(3) Depressed	(4) Depressed	(5) Depressed
Death of a household member	0.045***		0.044***	0.041***	0.038***
	(0.014)		(0.014)	(0.013)	(0.012)
Loss of property		0.041*	0.040*	0.032	0.032**
		(0.021)	(0.021)	(0.023)	(0.015)
Controls	No	No	No	Yes	Yes
Time FE	No	No	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Observations	68102	68102	68102	68102	68102

Notes: This table reports panel data regression results on the relationship between shocks and mental health measured by reported depression estimated on five rounds of the NIDS data. Columns (1) and (2) report fixed effects results controlling for the death of a household member and loss of property, respectively. Column (3) presents fixed effects results controlling for both shocks simultaneously. Column (4) reports fixed effects results controlling for shocks and other mental health covariates. Column (5) presents results from the correlated random effects estimator controlling for shocks and other covariates. Standard errors reported in parentheses are clustered at the district council municipality level. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

The NIDS data document information on the cause of death of deceased household members, i.e., whether death occurred due to accident/violence or natural causes, and the relationship of the deceased to the respondent. To explore some of the pathways by which the death of a household member is correlated with mental health, we control for these variables in the fixed effects and correlated random effects regressions and report the results in Table 4. The results suggest that death due to an accident or violence has a much stronger association with mental health. Fixed effects results reported in column 2 shows that experiencing the death of a household member due to an accident or violence increases the CES-D score of the average respondent by about 0.58. This represents an 8.3% increase in the CES-D score and almost a 165% increase in the coefficient size compared to the same fixed effects results reported in column 4 of Table 2.

The coefficient of experiencing the death of a household member due to an accident or violence on feeling depressed also increases by 173% (from 0.041 in column 4 of Table 3 to 0.112 in column 5 of Table 4). The results are consistent with previous studies that study the impact of the unanticipated loss of loved ones on mental health. For example, Siflinger (2017) uses panel data from the health and retirement survey (HRS) of the United States, matched with administrative data from the National Death Index to study the impact of the death of a spouse on the mental health of the surviving spouse. The author finds that experiencing the death of a spouse increases the risk of depression (measured on a 0, 1 binary scale) by 15.5 percentage points. In addition, the unexpected death of a spouse increases the risk of depression in the surviving spouse by additional nine percentage points.

Table 4: Shocks by cause and mental health: Panel data regressions

	(1) CES-D score	(2) CES-D score	(3) CES-D score	(4) Depressed	(5) Depressed	(6) Depressed
Death due to accident/violence	0.630**	0.576**	0.512***	0.119***	0.112**	0.109***
	(0.249)	(0.256)	(0.182)	(0.042)	(0.044)	(0.036)
Death of livestock/crop failure	0.111	0.136	0.136	0.035	0.023	0.024
	(0.236)	(0.240)	(0.116)	(0.040)	(0.043)	(0.022)
Controls	No	Yes	Yes	No	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68102	68102	68102	68102	68102	68102

Notes: This table reports panel data regression results on the relationship between shocks by cause and mental health. Columns (1) and (2) present fixed effects results controlling for shocks by cause and other covariates of mental health measured by the CES-D score, respectively. Column (3) reports correlated random effects results controlling for shocks by cause and other covariates. Columns (4) - (6) report similar regression results to columns (1) - (3) for mental health measured by reported depression. Standard errors reported in parentheses are clustered at the district council municipality level. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

The nature of the relationship between the deceased and the respondent, i.e., whether the deceased was a close household member or not, may also matter in analyzing the links between the death of a household member and mental health. In Table 5, we control for the nature of the relationship between the deceased and the respondent (i.e., whether the deceased is a spouse, son/daughter, or parent) and run regressions for both the CES-D and reported depression. The results suggest that the magnitude of the coefficient on the death of a household member gets larger when the deceased is a close family member. Compared to the main fixed effects and CRE results reported in columns 4 and 5 of Table 2, the coefficients in columns 2 and 3 of Table 5 are 35% and 28% larger, respectively. Experiencing the death of a close member is also strongly associated with feeling depressed. The fixed effects and CRE coefficients in columns 5 and 6 of Table 5 are 24% larger compared to the coefficients reported in columns 4 and 5 of Table 3.

Table 5: Death of close family member and mental health: Panel data regressions

	(1) CES-D score	(2) CES-D score	(3) CES-D score	(4) Depressed	(5) Depressed	(6) Depressed
Death of very close family member	0.541***	0.292**	0.264**	0.085***	0.051**	0.047**
	(0.135)	(0.119)	(0.106)	(0.024)	(0.021)	(0.020)
Loss of property	-0.043	0.046	0.022	0.039*	0.033	0.033**
	(0.160)	(0.150)	(0.082)	(0.021)	(0.023)	(0.015)
Controls	No	Yes	Yes	No	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68102	68102	68102	68102	68102	68102

Notes: This table reports panel data regression results on the relationship between the death of a close family member and mental health. Columns (1) and (2) present fixed effects results controlling for shocks and other covariates of mental health measured by the CES-D score, respectively. Column (3) reports correlated random effects results controlling for shocks and other covariates. Columns (4) - (6) report similar regression results to columns (1) - (3) on mental health measured by reported depression. Standard errors reported in parentheses are clustered at the district council municipality level. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

3.2. Robustness Checks

In this section, we investigate the robustness of our results to two key changes concerning the empirical strategy and the sample accounting for non-random attrition. First, we redefine the outcome variable. Reported depression is assumed to be cardinal in the preceding fixed effects regression analysis. However, the variable is ordinal; in response to the statement "I felt depressed", the respondent chooses responses from the options "rarely or none of the time = 1", "some or little of the time = 2", "occasionally or a moderate amount of time = 3", and "all the time = 4". Estimating the regression using linear models such as the fixed effects estimator assumes, for example, that an individual responding "all the time = 4" is twice as depressed as an individual who responds "some or little of the time = 2". In the framework of subjective response analysis, however, the dependent variable is assumed to be an unobserved latent outcome conventionally proxied by a self-reported mental health status response on an ordinal scale with various alternative categories. Therefore, the estimation procedure we discuss in detail in Appendix B needs to account for the ordered nature of the dependent variable.

Table 6 presents results from the random effects ordered probit estimator and the corresponding marginal effects on the association between shocks and depression. The results confirm the findings from the fixed effects regressions reported above – idiosyncratic shocks have a significant negative relationship with the mental health of individuals. In addition, loss of property, which was weakly significant in the fixed effects regression, is strongly statistically significant in the random effects ordered probit regressions. More specifically, the marginal effects reported in columns 2-5 suggest that a respondent who experienced the death of a household member has a 2.3 percentage point lower probability of reporting rarely feeling depressed and a 1 percentage point higher likelihood of reporting feeling depressed. Given the mean value of feeling depressed some of the time is 0.29 (Table 1), one percentage point translates to about a 3.5% increase. Similarly, the probability that a respondent experiencing the loss of property reports rarely feeling depressed is three percentage points lower, and the likelihood that the respondent reports sometimes feeling depressed is 1.3 percentage points higher (equivalent to a 5% increase).

Table 6: Shocks and mental health: Random effects ordered probit regression results

	[Parameter Estimates]	[Marginal Effects]			
	(1) [Estimates]	(2) [Rarely]	(3) [Some]	(4) [Moderate]	(5) [All the Time]
Death of a household member	0.062***	-0.023***	0.010***	0.009**	0.004***
	(0.015)	(0.005)	(0.002)	(0.002)	(0.001)
Loss of property	0.078***	-0.030***	0.013***	0.011***	0.005***
	(0.019)	(0.007)	(0.003)	(0.003)	(0.001)
Controls	Yes	-	-	-	-
DC Municipality FE	Yes	-	-	-	-
Time FE	Yes	-	-	-	-
Individual FE	Yes	-	-	-	-
Log Pseudolikelihood	-68980.07	-	-	-	-
Observations	68102	68102	68102	68102	68102

Notes: This table reports random effects ordered probit regression results and the corresponding marginal effects on the relationship between shocks and mental health estimated using five rounds of the NIDS data. Column 1 reports the parameter estimates on the relationship between shocks and feeling depressed. Columns 2 - 5 show the corresponding marginal effects on the four categories of feeling depressed ("rarely or none of the time", "some or little of the time", "occasionally/moderate amount of time", and "all the time" respectively). Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Second, to check for a possible bias resulting from non-random sampling, we conduct two types of tests: attrition test using the Wooldridge method (Wooldridge, 2010), and estimation of our key results reported in Table 2 using a sub-sample of respondents surveyed three times and five times, respectively. Columns 1 and 2 of Table 7 present attrition test results proposed by (Wooldridge, 2010). The coefficient for the number of subsequent waves the respondent is observed in the data is statistically insignificant, which suggests that our results are unlikely to be biased due to attrition.

As an additional check for the possible impact of attrition, we re-estimate the key results reported in Tables 2 and 3 using the sample of respondents observed three times and five times. The results reported in Tables C.1 and C.2 of the appendix show that the estimated parameter coefficients for the two explanatory variables of interest (death of a household member and loss of property) on the CES-D score are similar for the two sub-samples. Note that the sub-sample of respondents surveyed five times is twice as large as that of respondents surveyed three times. However, there is a relatively large difference in the coefficient for experiencing property loss between the two sub-samples, especially in columns (3) and (4), which report fixed effects regression on feeling depressed. These coefficients were not statistically significant in Table C.2 at conventional levels. Taken together, the results suggest that attrition is unlikely to significantly bias the main results on the relationship between shocks and the CES-D score.

Table 7: Shocks and mental health: Additional Robustness Checks

	(1) CES-D score	(2) Depressed	(3) lnCES-D Score
Death of a household member	0.215***	0.041***	0.004***
	(0.075)	(0.013)	(0.001)
Loss of property	0.042	0.032	-0.000
	(0.150)	(0.023)	(0.002)
Number of subsequent waves after t period	0.119	0.001	
	(0.082)	(0.015)	
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Observations	68102	68102	65266

Notes: This table reports robustness check regression results. Columns (1) and (2) present fixed effects results based on CES-D and reported depression, respectively controlling for the number of subsequent waves after each time and other covariates. The number of subsequent waves after each time is included to test for attrition bias, as suggested by Wooldridge (2010). Column (3) presents estimates using the fixed effects Poisson estimator. Standard errors reported in parentheses are clustered at the district council municipality level for estimations in columns (1) and (2), while robust standard errors are reported in column (3). ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Finally, based on an inspection of the distribution of the dependent variable (CES-D score), it is plausible to argue that it may not be distributed normally. As a robustness check, we estimate the fixed effects regression for the log of mental health, assuming a Poisson distribution. The results are reported in column 2 of Table 7 and remain robust.[7]

3.3. Discussion and Plausible Mechanisms

We analyzed the relationship between idiosyncratic shocks (the death of a family member and loss of property) and mental health measured by the Center for Epidemiological Studies – Depression Scale (CES-D) and reported depression using rich data from South Africa. We find a consistent negative relationship between the death of a household member and the mental health of respondents measured in both indicators. The coefficient of the death of a household member more than doubles when death happens due of an accident or violence. The coefficient also increases when the deceased is a close family member of the respondent. Loss of property did not seem to be associated with the CES-D score, but it is strongly associated with poor mental health when it is measured in the four-scale depression measure.

To establish a causal relationship, the fixed effects and the correlated random effects estimators assume strict exogeneity of the right-hand side variables. In the context of equation 1, and shocks, strict exogeneity implies that $E(u_{it}|\boldsymbol{Shocks_i}, \boldsymbol{X_i}, c_i) = 0, t = 1, \dots, T$. Given the focus of the paper on shocks, strict exogeneity, therefore, implies $E(\boldsymbol{Shocks}'_{\boldsymbol{it}}\boldsymbol{u_{it}}) = 0$, i.e., $\boldsymbol{Shocks}$ in any period should not be correlated with the idiosyncratic error term in any period. However, shocks may be correlated with the idiosyncratic error term because past shocks may affect current shocks and current mental health. Because of this, it is important not to treat α, the vector of coefficients for shocks, as causal estimates. We rather attempt to draw on existing studies and some descriptive regressions to shed light on the key plausible pathways through which experiencing the death of a household member may affect the mental health of the remaining household members.

The first plausible mechanism is likely the psychological pain of bereavement or grief, especially when unexpected. This pathway is documented by previous research in various health, psychology, and psychiatry disciplines. Earlier studies (Brent et al., 1994; Burton et al., 2006; Newson et al., 2011) provide evidence linking the unexpected death of a family member and psychiatric disorders such as depression, anxiety symptoms, and prolonged grief reactions. Keyes et al. (2014) builds on these studies, uses a large population-based sample in the United

[7] We thank an anonymous reviewer for the suggestion.

States, and shows that unexpected death is the most notable traumatic experience respondents experience. The authors find a strong association between the unexpected death of a loved one and an elevated risk for several psychiatric disorders, such as mania, depression, anxiety, and substance use. In economics, Siflinger (2017) shows that the risk of depression increases by 15.5 percentage points when a person loses their spouse. Sudden death increases the risk of depression by additional nine percentage points. Consistent with previous studies, we find that the correlation between the death of a household member and mental health increases significantly when the household member dies due to an accident or violence (i.e., when death is unanticipated) and when the deceased is a close family member of the respondent.

The second possible pathway that links the death of a household member to mental health would likely be through the loss of income when either the deceased had been the household breadwinner or contributed to household income significantly. There is substantial development literature documenting strong links between the death of a household member (more importantly, the death of a household head) and the decline in the economic status of the remaining household members (Dercon et al., 2005; Beegle et al., 2008; Dercon, 2008; Khan et al., 2015), and poor long-term outcomes of children (Case et al., 2004; Dercon, 2008; De Vreyer and Nilsson, 2019). A separate strand of research in various disciplines, such as public health, psychology, and economics (Clarke and Smith, 2000; Cai, 2009; Wahlbeck et al., 2017; Laura Shields-Zeeman, 2021) also investigates the impact of income on mental health. More recently, drawing on systematic review and meta-analysis of studies on income and mental health in various disciplines, Thomson et al. (2022) also establish a strong and uni-directional causal relationship between income and mental health – a change in income is followed by a significant change in wellbeing and mental health.

We attempt to offer suggestive evidence for the income pathway in the NIDS data in Table 8. Suppose loss of income is one pathway linking a household member's death to mental health. If that is the case, one should find a relationship between the variation in per capita income and the death of a household member on the one hand and between mental health and per capita income on the other.[8] In columns (1) and (2) of Table 8, we run the log of per capita income on the death of a household member using the fixed effects estimator. We find that the death of a household member is strongly negatively correlated with income per capita. In

[8] We thank two anonymous reviewers for suggesting the exercise and providing guidance.

columns (3) and (4), we also show a robust negative relationship between the log of per capita income and the CES-D score controlling for the residuals generated from columns (1) and (2). Given that the fixed effects estimator works through a with-in transformation, the results presented in Table 8 offer suggestive evidence of the relationship between the death of a household member and the CES-D score through income.

Table 8: Shocks and mental health: Plausible Mechanisms

	(1) lnPCINC	(2) lnPCINC	(3) CES-D score	(4) CES-D score
Death of a household member	-0.145***	-0.061***		
	(0.023)	(0.015)		
lnPCINC			-0.302***	-0.161***
			(0.059)	(0.043)
Residuals			-1.931 ***	-3.567 ***
			(0.527)	(1.235)
Controls	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	68102	68102	68102	68102

Notes: This table reports fixed effects regression results exploring plausible mechanisms. Column (1) presents regression results on the links between the log of per capita income in levels and the death of a household member. Column (2) reports the same results controlling for covariates. Column 3 reports results on the links between the log of per capita income and CES-D score controlling for the residuals from column (1). Column (4) presents the same results as in column (3) controlling for the residuals from column (2) and other controls. Standard errors reported in parentheses are clustered at the district council municipality level. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

4. Conclusions

The prevalence of mental health disorders is on the rise worldwide, and understanding the role of adverse events on mental health is crucial to design appropriate interventions. This is particularly important for most households in developing countries, who often are vulnerable to shocks but do not have formal insurance and access to treatment to cope with them. This paper uses five rounds of rich panel data from South Africa to study the relationship between idiosyncratic shocks and mental health as measured by the Center for Epidemiological Studies Depression Scale (CES-D) and reported depression. We estimate alternative linear panel data regressions to explore the relationship between shocks and mental health. We also tested our results' robustness using the random effects ordered probit estimator and conducted other key robustness checks. If idiosyncratic shocks have a strong relationship with wellbeing beyond consumption and income in a formally uninsured set-up, the welfare impact of safety net, insurance, and health interventions is likely much larger than has been documented by previous studies. Using robust panel data estimators from data in an African context, we show that idiosyncratic shocks are strongly correlated with poor mental health, which is the key contribution of our paper.

We find a strong relationship between the death of a household member and mental health. Regression results suggest that respondents who experienced the death of a household member report about 3.1% lower mental health score than those who did not experience the shock. However, experiencing the death of a household member due to an accident or violence increases the magnitude of the coefficient on the CES-D score and reported depression by about 165% and 173%, respectively. The coefficient of the death of a household member on the CES-D score and reported depression also increases by 35% and 24% when the deceased is a close family member (spouse, son/daughter, or parent). Taken together, the results provide suggestive evidence on the effects of the unanticipated death of a household member on mental health consistent with previous studies (e.g., Brent et al., 1994; Burton et al., 2006; Newson et al., 2011; Siflinger, 2017). Regression results from the random effects ordered probit estimator also suggest that property loss is associated with poor mental health when mental health is measured on a four-level depression scale.

Important recent literature in developing countries (Adhvaryu et al., 2019; Singhal, 2019; Alloush and Bloem, 2022) documents that covariate shocks negatively impact individuals' mental health. Our study shows that idiosyncratic shocks are strongly correlated with poor mental health. The large increase in the coefficient of the death of a household member when death is unanticipated and when it occurs to a close family member suggests that one of the pathways by which death affects mental health is through the psychological pain of bereavement or grief. This offers suggestive evidence that the impact of shocks on household welfare likely extends beyond income, consumption, education, and technology adoption – the commonly investigated outcome variables of interest. Given mental health disorders result in significant economic loss to society, this, in turn, implies that additional large welfare gains can be made from informal (traditional) therapeutic networks and mental health interventions. The proportion of households with access to psychiatric or therapeutic care in Africa is tiny because the amount of resources allocated to mental health care is less than 1% of the healthcare budget (Sankoh et al., 2018). Consequently, only less than 2% of the population that suffers from mental illness receives treatment. In South Africa, the most economically advanced country in Sub-Saharan Africa, 75% of the population does not have access to psychiatric or therapeutic care (Gberie, 2017). The government can substantially reduce the effect of shocks on mental health by putting conducive policies that encourage the expansion of psychiatric and therapeutic interventions in place.

We also attempted to shed light on the second possible pathway by which the death of a household member may affect mental health – economic hardship because of loss of income. If income loss due to the death of a breadwinner significantly affects the mental health of the remaining household members, which it does according to systematic review studies (Thomson et al., 2022), the provision of safety nets to vulnerable citizens whose income is reduced due to shocks is crucial. South Africa's safety net programs are more advanced than many SSA countries. Nevertheless, there seems to be much room for improved welfare through expanding social support and safety nets and reducing the impact of shocks on mental health.

There is a large scope for future research on the magnitude of the impact of idiosyncratic shocks on the mental health of households in developing countries using improved identification strategies. There has been a significant surge of household panel data sets collected by statistics offices of many SSA countries in the past decade, supported by international institutions, such as the World Bank. Although comprehensive and valuable for analyzing different socioeconomic issues, these surveys do not collect any mental health-related information. Mental health disorders are on a sharp rise in the continent. For example, African countries account for half of the top 30 countries with the highest rate of suicide (WHO, 2020). Unless addressed swiftly by allocating more resources to mental health care, such a trend will have significant adverse effects on the already fragile economies of many African countries. More research on mental health, the causes and consequences of mental health disorders, and treatment options in the continent is urgently needed.

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Appendix A: Regressions with All Control Variables

Table A.1: Shocks and mental health: Panel data regressions

	(1) FE-1 CES-D score	(2) CRE-1 CES-D score	(3) FE-2 Depressed	(4) CRE-2 Depressed
Death of a household member	0.217***	0.207***	0.041***	0.038***
	(0.076)	(0.063)	(0.013)	(0.012)
Loss of property	0.042	0.017	0.032	0.032**
	(0.150)	(0.082)	(0.023)	(0.015)
Household income/capita (log)	-0.162***	-0.158***	-0.022***	-0.021***
	(0.042)	(0.030)	(0.006)	(0.006)
Years of schooling	-0.001	0.010	0.006	0.005
	(0.025)	(0.022)	(0.004)	(0.004)
Age	-0.220*	-0.243***	0.014	0.013
	(0.110)	(0.057)	(0.016)	(0.010)
Age square of the respondent	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.000 (.)	0.212***	0.000	0.034***
		(0.036)	(.)	(0.007)
Married	-0.494***	-0.440***	-0.039***	-0.033**
	(0.090)	(0.087)	(0.014)	(0.016)
Widowed or separated	0.068	0.095	0.019	0.026
	(0.172)	(0.130)	(0.030)	(0.025)
Unemployed	-0.365***	-0.371***	-0.029	-0.025**
	(0.097)	(0.061)	(0.018)	(0.012)
Employed	-0.388***	-0.400***	-0.039***	-0.042***
	(0.076)	(0.059)	(0.013)	(0.011)
African	0.000	1.176***	0.000	0.081***
	(.)	(0.073)	(.)	(0.013)
Urban	0.079	0.183	0.069**	0.044*
	(0.158)	(0.122)	(0.030)	(0.024)
Observations	68102	68102	68102	68102.000

Notes: This table reports panel data regression results on the relationship between shocks and mental health measured by the CES-D score and reported depression estimated on five rounds of the NIDS data. Columns (1) and (3) report fixed effects results on the relationship between idiosyncratic shocks and mental health (CESD score and reported depression, respectively) accounting for the full set of control variables. Columns (2) and (4) report correlated random effects results on the relationship between idiosyncratic shocks and mental health (CESD score and reported depression, respectively) accounting for the full set of control variables. Standard errors reported in parentheses are clustered at the district council municipality level. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A.2: Shocks by cause and mental health: Panel data regressions

	(1) FE-1 CES-D score	(2) CRE-1 CES-D score	(3) FE-2 Depressed	(4) CRE-2 Depressed
Death due to accident/violence	0.576**	0.512***	0.112**	0.109***
	(0.256)	(0.182)	(0.044)	(0.036)
Death of livestock/crop failure	0.136	0.136	0.023	0.024
	(0.240)	(0.116)	(0.043)	(0.022)
Household income/capita (log)	-0.165***	-0.161***	-0.022***	-0.022***
	(0.042)	(0.030)	(0.006)	(0.006)
Years of schooling	-0.000	0.010	0.006	0.006
	(0.025)	(0.022)	(0.004)	(0.004)
Age	-0.219*	-0.241***	0.014	0.012
	(0.110)	(0.057)	(0.016)	(0.010)
Age square of the respondent	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.000 (.)	0.210***	0.000	0.033***
		(0.036)	(.)	(0.007)
Married	-0.503***	-0.447***	-0.041***	-0.034**
	(0.089)	(0.087)	(0.014)	(0.016)
Widowed or separated	0.085	0.112	0.022	0.029
	(0.175)	(0.130)	(0.031)	(0.025)
Unemployed	-0.364***	-0.370***	-0.028	-0.025**
	(0.098)	(0.061)	(0.018)	(0.012)
Employed	-0.388***	-0.401***	-0.039***	-0.041***
	(0.077)	(0.059)	(0.013)	(0.011)
African	0.000 (.)	1.178***	0.000	0.081***
		(0.073)	(.)	(0.014)
Urban	0.081	0.183	0.068**	0.044*
	(0.158)	(0.122)	(0.030)	(0.024)
Observations	68102	68102	68102	68102

Notes: This table reports panel data regression results on the relationship between shocks and mental health measured by the CES-D score and reported depression estimated on five rounds of the NIDS data. Columns (1) and (3) report fixed effects results on the relationship between idiosyncratic shocks and mental health (CESD score and reported depression, respectively) accounting for the full set of control variables. Columns (2) and (4) report correlated random effects results on the relationship between idiosyncratic shocks and mental health (CESD score and reported depression, respectively) accounting for the full set of control variables. Standard errors reported in parentheses are clustered at the district council municipality level. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Table A.3: Death of close family member and mental health: Panel data regressions

	(1) FE-1 CES-D score	(2) CRE-1 CES-D score	(3) FE-2 Depressed	(4) CRE-2 Depressed
Death of very close family member	0.292**	0.264**	0.051**	0.047**
	(0.119)	(0.106)	(0.021)	(0.020)
Loss of property	0.046	0.022	0.033	0.033**
	(0.150)	(0.082)	(0.023)	(0.015)
Household income/capita (log)	-0.164***	-0.160***	-0.022***	-0.022***
	(0.043)	(0.030)	(0.006)	(0.006)
Years of schooling	-0.001	0.009	0.006	0.005
	(0.025)	(0.022)	(0.004)	(0.004)
Age	-0.219*	-0.241***	0.014	0.013
	(0.110)	(0.057)	(0.016)	(0.010)
Age square of the respondent	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.000 (.)	0.213***	0.000	0.034***
		(0.036)	(.)	(0.007)
Married	-0.493***	-0.439***	-0.039***	-0.033**
	(0.089)	(0.087)	(0.014)	(0.016)
Widowed or separated	0.061	0.091	0.018	0.026
	(0.173)	(0.131)	(0.030)	(0.025)
Unemployed	-0.364***	-0.370***	-0.028	-0.025**
	(0.097)	(0.061)	(0.018)	(0.012)
Employed	-0.388***	-0.400***	-0.039***	-0.042***
	(0.076)	(0.059)	(0.013)	(0.011)
African	0.000 (.)	1.176***	0.000	0.081***
		(0.073)	(.)	(0.013)
Urban	0.076	0.181	0.068**	0.044*
	(0.158)	(0.122)	(0.030)	(0.023)
Observations	68102	68102	68102	68102

Notes: This table reports panel data regression results on the relationship between shocks and mental health measured by the CES-D score and reported depression estimated on five rounds of the NIDS data. Columns (1) and (3) report fixed effects results on the relationship between idiosyncratic shocks and mental health (CESD score and reported depression, respectively) accounting for the full set of control variables. Columns (2) and (4) report correlated random effects results on the relationship between idiosyncratic shocks and mental health (CESD score and reported depression, respectively) accounting for the full set of control variables. Standard errors reported in parentheses are clustered at the district council municipality level. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.

Appendix B: Random Effects Ordered Probit Estimator

We redefine the outcome variable. Reported depression is assumed to be cardinal in the preceding fixed effects regression analysis. However, the variable is ordinal in nature; in response to the statement "I felt depressed", the respondent chooses responses from the options "rarely or none of the time = 1", "some or little of the time = 2", "occasionally or a moderate amount of time = 3", and "all the time = 4". Estimating the regression using linear models such as the fixed effects estimator assumes, for example, that an individual responding "all the time = 4" is twice as depressed as an individual who responds "some or little of the time = 2". In the framework of subjective response analysis, however, the dependent variable is assumed to be an unobserved latent outcome conventionally proxied by a self-reported mental health status response, D^*, on an ordinal scale with various alternative categories. The estimation procedure therefore needs to account for the ordered nature of the dependent variable

We specify a model of a latent linear response, where observed ordinal responses D_{it} are generated from the latent continuous responses, such that

$$D_{it}^* = \alpha Shocks_{it} + \beta X_{it} + \gamma Wave + \eta Cluster + c_i + u_{it} \quad (1)$$

and

$$D_{it} = \begin{cases} 1 & if\ D_{it}^* \leq k_1; \\ 2 & if\ k_1 < D_{it}^* \leq k_2; \\ & \vdots \\ K & if\ k_{K-1} < D_{it}^*. \end{cases} \quad (2)$$

The error term $u_{it} \sim (0, 1)$, and is independent of the unobserved individual heterogeneity c_i. The remaining terms and parameters are as defined in equation 1.

The conditional distribution for response D_{it}, given the panel-level random effects c_i can bespecified as

$$f(D_{it}, k, x_{it}\beta - c_i) = \prod_{K=1}^{K} p_{itk}^{I_k(D_{it})} = exp \sum_{k=1}^{K} \{I_k(D_{it}) \log(p_{itk})\} \quad (3)$$

where

$$I_k(D_{it}) = \begin{cases} 1 & if\ D_{it} = k \\ 0 & otherwise \end{cases} \tag{4}$$

Given equations 2 - 4, one can specify the conditional distribution of di and the panel likelihood function li and can use the Gauss-Hermite quadrature to approximate the solution and estimate the parameters from a maximum likelihood estimator. One can then compute the corresponding marginal effects, which, when multiplied by 100, show the percentage point change in the probability of belonging to a particular depression category for a marginal change in the explanatory variables of interest.

Appendix C: Additional Attrition Analysis

Table C.1: The impact of shocks on mental health: Fixed effects regressions

	(1) CES-D score	(2) CES-D score	(3) Depressed	(4) Depressed
Experienced death of a household member	0.439** (0.206)	0.376* (0.207)	0.044 (0.034)	0.045 (0.034)
Experienced loss of property	-0.079 (0.261)	-0.137 (0.243)	0.082* (0.045)	0.063 (0.046)
Controls	No	Yes	No	Yes
DC Municipality FE	No	Yes	No	Yes
Time FE	No	Yes	No	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	12690	12690	12690	12690

Notes: This table reports fixed effects regressions on the relationship between shocks and mental health estimated using sub-sample of NIDS data observed only in three rounds of the five waves. Column 1 reports the impact of shocks on CES-D score without controlling for covariates and round fixed effects. Column 2 reports the same regression controlling for covariates and round fixed effects. Column 3 reports the impact of shocks on reported state of depression without controlling for covariates and round fixed effects. Column 4 reports the same regression controlling for covariates and round fixed effects. Standard errors reported in parentheses are clustered at the district council municipality level. ***, ** and * denote significance at the 1, 5, and 10% levels, respectively.

Table C.2: The impact of shocks on mental health: Fixed effects regressions

	(1) CES-D score	(2) CES-D score	(3) Depressed	(4) Depressed
Experienced death of a household member	0.545***	0.377***	0.080***	0.070***
	(0.091)	(0.097)	(0.018)	(0.018)
Experienced loss of property	-0.092	0.064	0.013	0.014
	(0.195)	(0.189)	(0.028)	(0.030)
Controls	No	Yes	No	Yes
Time FE	No	Yes	No	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	26020	26020	26020	26020

Notes: This table reports fixed effects regressions on the relationship between shocks and mental health estimated using sub-sample of NIDS data observed in all rounds of the five waves. Column 1 reports the impact of shocks on CES-D score without controlling for covariates and round fixed effects. Column 2 reports the same regression controlling for covariates and round fixed effects. Column 3 reports the impact of shocks on reported state of depression without controlling for covariates and round fixed effects. Column 4 reports the same regression controlling for covariates and round fixed effects. Standard errors reported in parentheses are clustered at the district council municipality level. ***, ** and * denote significance at the 1, 5, and 10% levels, respectively.

Chapter Three

Early Life Shock and Labour Market Outcomes: Panel Data Evidence from South Africa

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Abstract

Adverse life events have short- and long-term effects on the livelihood of victims. This paper studies the effect of early life idiosyncratic shocks on labour market outcomes using five rounds of panel data from the National Income Dynamics Study (NIDS) of South Africa. Regression results from alternative panel data estimators suggest that the loss of biological parents early in life is negatively associated with the likelihood of employment and wage earnings. The association is stronger when one loses one's biological mother than one's biological father. Heterogeneity analysis reveals that the loss of a biological father among Black South Africans leads to higher wage earnings compared to other race groups who have experienced the same shock. Education level, perceived health, cognitive ability, and occupation type are strongly associated with the loss of a biological mother, while only education is associated with the loss of a father. These could be the main channels that mediate the link between early life loss of biological parents and labour market outcomes. Therefore, strengthening and aligning child support programmes to reach the victims are required.

KEYWORDS: Early life shock; death; earnings; unemployment; South Africa

JEL CLASSIFICATION CODES: I12; I26; J21; J31; O15

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1. Introduction

Adverse events in life are common in developing countries where their short- and long-term impact on the livelihood of people is paramount. The prominent shocks experienced by households in developing countries include weather shocks (Abiona, 2017; Maccini & Yang, 2009), agricultural commodity price volatility (Adhvaryu et al., 2019), famine (Ampaabeng & Tan, 2013; Dercon & Porter, 2014), and armed conflict (Singhal, 2019). Health-related idiosyncratic shocks such as illness and mortality are also worth mentioning (Alem & Tato, 2023; Maccini & Yang, 2009). Evidence shows that the livelihood systems of victims affected by these shocks are eroded keeping them in perpetual poverty with possible inter-generational impact (Alam, 2015; Andersen, 2013; Bratti & Mendola, 2014; Lindo, 2011). One of the main reasons why such shocks have a long-lasting impact in a developing country context is due to the lack or shortage of formal insurance mechanisms against such shocks (Jensen & Barrett, 2017; Jung & Tran, 2012; Mobarak & Rosenzweig, 2013; Robinson, 2012).

The association between early-life shock and late-life outcomes is a recent phenomenon that has received little investigation. Early life rainfall shock has been identified as a prominent factor affecting health, education, and other socioeconomic outcomes (Abiona, 2017; Adhvaryu et al., 2018; Maccini & Yang, 2009). Adhvaryu et al. (2019) showed the adverse effect of early-life cocoa price volatility on psychological well-being in Ghana. Singhal (2019) has also found an adverse effect of early life war experience on mental health. The effect of early life famine experience is also proved to have an impact on the physical height of victims (Dercon & Porter, 2014), adult health (Kesternich et al., 2015), cognitive ability (Ampaabeng & Tan, 2013), and survival at older ages (Lindeboom et al., 2010). Similarly, idiosyncratic shocks such as the loss of parents during childhood are associated with late-life psychiatric disorders (M. J. Gay & Tonge, 1967; Harris et al., 1986, 1990), health, and education (Beegle et al., 2010). Contemporaneous shocks such as parental unemployment (Andersen, 2013) and health shock (Alam, 2015; Bratti & Mendola, 2014) also determine children's education outcomes. Among the very few studies that link idiosyncratic shock with labour market indicators, Börner et al. (2015) considered household labour reallocation, while Heltberg and Lund (2009) used child labour as an outcome variable.

Though the broader literature suggests the adverse effects of idiosyncratic shocks on the livelihood of victims, it is not obvious if such shocks necessarily lead to long-lasting impacts as there could be insurance mechanisms for mitigation. With very limited formal insurance systems in developing countries, informal insurances are available to mitigate the effect of such shocks (Abrokwah et al., 2019; Dercon, 2005; Heltberg & Lund, 2009; Robinson, 2012). It is, therefore, worth extending the literature to explore the effect of idiosyncratic shocks on socio-economic outcomes. This paper uniquely investigates the effect of an early-life idiosyncratic shock (loss of biological parents) on late-life labour market outcomes. In doing so, it contributes to the body of literature in development economics by providing empirical evidence on why some people succeed in the labour market while others do not. This is more relevant in a developing country context where labour, which is the main asset for the poor, is the main source of income for the livelihood of individuals and households. For instance, labour income accounts for more than half of the total household income in low- and middle-income countries (Fields, 2012; van Treeck, 2019). Fields (2012) thus underlines the importance of understanding labour markets and labour earnings in developing countries to understand global poverty. The paper also contributes to the broader shock literature by capturing a permanent shock of parental death unlike most temporary shocks covered by the literature.

This study also contributes to the literature on early-life shock and labour market outcomes in developing countries by utilising very rich panel data from South Africa. South Africa is a great setting for investigating the relationship between orphanhood and late-life labour market challenges, as both are pervasive. South Africa, like other sub-Saharan African countries, has seen a significant increase in orphanages, putting millions of children at risk, particularly as the HIV/AIDS pandemic has spread (Ardington & Leibbrandt, 2010; Bozzoli, 2016; Bray, 2003; Chuong & Operario, 2012). South Africa, whose formal sector employment accounts for around 70% of the total employed labour force (Statistics South Africa, 2021), is also known for its persistently high unemployment rate and wage inequalities. As a result, the formal labour market in South Africa is thought to be the most important predictor of the country's socio-economic status (Ranchhod & Daniels, 2021). According to Mosomi and Wittenberg (2020), South Africa's aggregate unemployment rate was 31.5% in 2003, 21.5% in 2008, and 27.9% in 2017. The 2020 unemployment rate was 29.4% (Statistics South Africa, 2020). On the other hand, there is a considerable level of wage inequality in the country, with employees in the 90th percentile earning four and six times more than those at the median in 2000 and 2015, respectively (Mosomi & Wittenberg, 2020). In addition to the availability of rich data, using South Africa as a case study provides an excellent example in terms of capturing the labour market outcomes and drawing relevant lessons for other developing nations.

This paper explores the effect of an early life shock (loss of biological parents in childhood) on wage earnings and unemployment during adulthood using the South African National Income Dynamics Study (NIDS) survey conducted in five rounds (2008 - 2017). To account for the time-invariant nature of the interest variable, early life loss of biological parents, while accounting for the fixed effect of time-varying covariates, we used the Correlated Random Effect (CRE) estimator proposed by Mundlak (1978) and Chamberlain (1982). The results from the CRE and other alternative estimations reveal the presence of a statistically significant association between the death of biological parents and monthly wage earnings. Adult respondents who have lost their biological mother during early childhood have a 22% lower monthly wage than their counterparts, while the difference is only about 13% for those who have lost their biological father. Unemployment is also found to be correlated with the shock variables.

Results from heterogeneous analysis reveal that Black South Africans who lost their biological father early in life earn higher wages than those in other race categories who have experienced the same shock. Alternative mechanisms were also checked to consider how shocks in the early life of the respondents affect their labour market outcomes later in life. We show that the main channel that links the loss of biological parents during early childhood with wage earning is the level of education. However, the perceived health, cognitive ability, and occupation type of respondents are also found to be channels that could explain the link when one loses a biological mother. It is, therefore, important to put safety net programmes in place with financial and psychological support to protect children at the time of death of their biological parents.

The rest of the paper is organized as follows. Section 2 reports the conceptual framework. Section 3 discusses the data and provides basic descriptions of the main variables used in the study. The empirical strategy is presented in Section 4. Section 5 presents and discusses the results from alternative estimators including heterogeneity analysis, robustness checks, and mechanisms. Conclusions and policy implications are presented in Section 6.

2. Conceptual Framework

In the conventional neoclassical explanation of wage determination market demand and supply of labour play an important role. In this circumstance, labourers decide how much labour to supply based on labour vs leisure hour optimization. However, firms' decision on how much labour to hire depends on factor productivity. That is, individual workers are usually argued to receive compensation equivalent to their productive contribution to a firm's output. Workers who are more productive and therefore contribute more to output would earn higher wages than those with lower levels of productivity. In light of claims that productivity difference is one of the main sources of wage differential among workers, it is natural to ask why there is variation in labour productivity. This leads to human capital theory, which is a standard theory of earnings (Avent-Holt & Tomaskovic-Devey, 2014).

Human capital theory, developed by Becker (1964) and Mincer (1974), explains that the wage differential across time and individuals is mainly due to change or variation in workers' accumulated skills (Burdett et al., 2011). According to this theory, younger people earlier in their labour market participation earn less due to their engagement in human capital investment which involves an opportunity cost. The stock of human capital accumulated in life, however, is not easy to aggregate from in-school and post-school investments alone as there are other disturbances and initial condition differences that contribute to human capital. Mincer (1974) indicates that the initial capacities of individuals and investments provided by the home environment could be the reasons behind the difficulty of aggregation. In support of this, Kao et al. (1994) argue that human capital is acquired not only from formal schooling and post-school training but also from family care in preschool years, health, and job search.

Earnings function based on human capital theory broadly suggests that investment in human capital determines wage earnings. More specifically, earning is modelled as a function of years of schooling and age. Years of schooling is a good indicator to capture the first phase of investment in human capital. On the other hand, age is assumed to capture net self-human capital investment activities after completion of schooling (Mincer, 1974). Most previous studies based on this theory consider the measurable components of human capital in explaining wage differentials. For instance, some studies link labour market outcomes to differences in education (Altonji et al., 2013; Álvarez & Palencia, 2018; de Baldini Rocha & Ponczek, 2011; Maitra & Mani, 2017; Tamborini et al., 2015), and health situations and shocks (Altonji et al., 2013; Brunello & d'Hombres, 2007; Garc\'\ia-Gómez, 2011; Paraponaris et al., 2005; Trevisan & Zantomio, 2016).

It is important to note, that the hypothesized association between human capital indicators and earnings hold if individual differences in ability and opportunity, which determines their investment behaviour, persist over their life cycle (Mincer, 1974). This implies that shocks that affect investment in human capital will also affect labour market outcomes. Beyond the effect of shocks during and post schooling, shocks and family situations before schooling are also worth looking at as they affect the early mental and physical development of children. In this regard, the role of parents is considered to be substantial. The transmission mechanism from parent to children could range from the mother's prenatal situations, breastfeeding, and diet to the way children are treated at home. One of the pioneers in human capital theory, Becker (1964), clearly explains the influence of families on the knowledge, skills, values, and habits of their children. According to Becker, a very small difference among children in the preparation provided by their families will lead to growing differences over time (Becker, 2009). Hence, it is possible to expect significant differences in treatment and preparation between children who lost either or both of their biological parents and those who did not. Such differences are expected to affect human capital development and thereby labour market outcomes. This paper, therefore, adds to the literature by exploring the effect of early-life idiosyncratic shock (loss of biological parents) on late-life labour market outcomes using a very rich data set from South Africa.

3. Empirical Strategy

We estimate labour market outcomes following human capital theory. In Mincer (1974) traditional human capital earnings equation, the wage of an individual can be modelled as a function of years of schooling and other individual characteristics. This earning equation can be specified as (Barth et al., 2018):

$$logW_{it} = \alpha + X_{it}\gamma + \mu_t + \epsilon_{it} \quad (1)$$

where $logW_{it}$ is the logarithm of wage earnings of individual i in period t. X_{it} is years of schooling and other individual attributes such as age, gender, and race of individual i at time t. μ_t is a time-specific fixed effect and ϵ_{it} is the composite error term containing individual specific effects and idiosyncratic errors.

In the traditional earnings equation, equation 1, years of schooling is one of the main factors behind variation in earnings. However, in this study, the early life idiosyncratic shock variables are hypothesized to affect labour market outcomes through their effect on human capital formation. Education, the main human capital indicator, correlates with the main variable of interest (early life shock) and outcome variable so including education would result in bad controls. Therefore, to have a clear interpretation of the effect of the shock variables on labour market outcomes, the estimation model is respecified and given in equation 2 as:

$$logW_{it} = \alpha + S_i\beta + X_{it}\gamma + \mu_t + \epsilon_{it} \tag{2}$$

where S_i is a vector of shock dummies measuring whether an individual has experienced early life shock or not. The shock variables considered are the death of the biological father and the death of the biological mother before the age of 5 years. X_{it} now includes both individual and household-specific attributes such as gender, marital status, age, race, and district municipality dummies, but not human capital indicators.

Given the panel nature of the data, random effect and fixed effect estimation approaches are appropriate. The distinction between random effect and fixed effect lies in the randomness of household-specific effects, which might not be the case most of the time. The standard fixed effects model could be used to account for the fixed effect of time-varying covariates. However, in this particular study, due to the time-invariant nature of the main independent variables, running a fixed effects model eliminates the coefficient of time-invariant independent variables. To combat this, as proposed by Mundlak (1978) and relaxed by Chamberlain (1980, 1982), a Correlated Random Effect (CRE) approach helps to account for the fixed effects of time-varying covariates while keeping the estimates of time-constant variables. More specifically, the approach has the flexibility advantage to estimate the effect of time-varying variables while providing effect estimates of time-invariant variables that are unbiased due to a possible correlation with time-varying unobserved heterogeneity (Schunck, 2013; Wooldridge, 2013). In the setup of this study, where panel data is used with time-invariant main independent variable, the effect of early life shock exploits the cross-sectional variation once the time and cross-sectional variations attributed by other time-variant and time-invariant control variables are accounted for. Therefore, the CRE model which is the main estimation approach for this study is specified as:

$$logW_{it} = \alpha + S_i\beta + Z_i\theta + X_{it}\gamma + \bar{X}_i\delta + T_t\mu + \varepsilon_{it} \tag{3}$$

where S_i is a vector of shock dummies which are time-invariant. Z_i is a vector of other time-constant factors like gender and race. X_{it} includes independent variables which change both across individual i and time t. The new term $\bar{X}_i$ is the vector of time averages of time-varying variables. T_t is a vector of aggregate time effects and ε_{it} is the error term.

Identification in both the fixed and random effects estimators requires the strict exogeneity assumption. In addition, the random effects estimator requires the orthogonality assumption. Therefore, the specification in equation 3 estimated using the CRE model that accounts for the fixed effect of time-varying regressors requires at least the shock variables to be exogenous, which is still hard to make. Therefore, the paper establishes an association between early-life shock and late-life labour market outcomes. However, causal implications are also drawn based on alternative estimations and hypothesis validations.

4. Data

This study uses five waves (2008 - 2017) of data from the National Income Dynamics Study (NIDS) of South Africa. In the first round in 2008, data was collected from more than 28,000 individuals in about 7,000 households across the country. The subsequent waves (2010/11, 2012, 2014/15 and 2017) used this initial sample of household members as Continuing Sample Members (CSM). Children born to CSM mothers are added as CSMs and tracked in subsequent waves. Other household members in the subsequent waves are considered Temporary Sample Members (TSMs) and not tracked. This study considers adult respondents from the continuing sample observed in at least two of the NIDS waves. 73% of the individuals from wave 1 were successfully interviewed in wave 5. 77%, 87%, and 92% of the individuals added as CSMs in the subsequent three waves were successfully interviewed in wave 5, respectively (Brophy et al., 2018). For this study, only adult respondents in the working-age group (15 to 64 years inclusive) are selected. To utilize the panel nature of the data, 16,923 uniquely identified working-age respondents observed in at least two waves and with full information, which sum to a total of 62,915 observations, are used for the analysis.

Our main dependent variable is wage earnings, though an unemployment dummy is also used as an alternative indicator. Total monthly take-home pay (earnings) is derived from primary and secondary employment, casual work, and self-employment through aggregation. Early life loss of biological parents, which is an idiosyncratic shock, is the main variable of interest hypothesized to affect labour market outcomes. The death of a biological father and mother before the respondents celebrated their fifth birthday are taken as regressors separately. A cut-off point of 5 years can be justified for two main reasons. First, at the time the shocks occurred the children were not eligible for schooling. In South Africa, education is compulsory for children between 5 and 15 years of age, with an official minimum age of 5 years old for starting preparatory grade (Grade R/0) (Statistics South Africa, 2017). Second, events before the age of five years have been shown to have a permanent effect on adult outcomes, particularly in shaping human capital development (Currie & Almond, 2011). As a robustness check, the age of 15 years (before respondents are formally eligible to enter the labour market) is also used as a cut-off point to construct the idiosyncratic shocks.

In the estimations, other control variables such as age, gender, marital status, race, province/district municipality, and time dummies are included to account for their effect. Though the focus of this paper is to thoroughly analyze the association between parental death and labour market outcomes, controlling for the attributes of other potential factors is important. For instance, the pioneer Mincer's (1974) traditional human capital equation considers age, gender, and race as potential attributes to earnings (Barth et al., 2018). Marital status is also considered an important factor behind variation in labour market outcomes (Brunello & d'Hombres, 2007; Kao et al., 1994; Maitra & Mani, 2017; Tamborini et al., 2015). Province and time dummies are included to account for region- and time-specific effects on labour market outcomes, respectively. Education level, perceived health, emotional well-being disorder, occupation type, and cognitive ability are used as possible mechanisms linking shocks with labour market outcomes. That is, early-life parental death, through its effect on human capital formation and related outcomes, could affect adulthood labour market outcomes.

5. Results and Discussion

5.1. Descriptive Statistics

Table 1 presents summary statistics of key variables for the pooled data set including the between and within standard deviations. With the notion of weather shocks and deaths of family members are commonly occurring shocks in developing countries, and in South Africa, as indicated in Column (1), about 18% of the respondents lost their biological father before they celebrated their 15th birthday, while about 8% lost their biological mother by the same age. Loss of a father and mother in early childhood (before the age of 5 years), on the other hand, is limited to about 6% and 2%, respectively.

The higher rate of death of men over women is consistent with data from the official South African statistical reports. According to a report by Maluleke (2016), for the period between 1997 and 2016 death of males was consistently higher than the death of females. For instance, the difference in the proportion of death between males and females for the years 1997 to 2000 was on average about 8.8 percentage points. During the same period, the main cause of death (more than 50% of deaths on average) in the country was due to non-communicable diseases, with a smaller proportion of death resulting from covariate shocks falling into the categories of war, famine, and other natural disasters. This fact reveals the importance of considering death due to idiosyncratic shocks and evaluating its long-term consequences.

Table 1: Summary Statistics of Pooled Data

	(1) Mean	(2) sd(Between)	(3) sd(Within)	(4) Obs.
Main Variables				
Father deceased before age 5	0.06	0.229	0	62915
Mother deceased before age 5	0.02	0.134	0	62915
Father deceased before age 15	0.18	0.388	0	62604
Mother deceased before age 15	0.08	0.271	0	62812
Monthly earnings (in SA Rand)	4043.90	5552.58	5075.07	24472
Unemployed dummy	0.16	0.219	0.230	62915
Other Controls				
Age	34.11	14.036	2.895	62915
Female	0.58	0.497	0	62915
Married	0.31	0.410	0.207	62915
Widowed or separated	0.07	0.218	0.132	62915
Single	0.61	0.444	0.193	62915
African	0.82	0.394	0	62915
Coloured	0.14	0.355	0	62915
Asian/Indian	0.01	0.114	0	62915
White	0.03	0.174	0	62915
Mechanisms				
Education level	9.97	3.670	0.845	62782
Perceived health	3.83	0.741	0.799	62826
Emotional well-being disorder	6.95	2.723	3.536	61611
Elementary occupation	0.33	0.424	0.242	23705
Financial literacy	2.14	1.078	0	12645

Notes: Column (1) reports the mean values of key variables. Columns (2) and (3) are the between and within standard deviation of the panel data, while column (4) shows the total number of observations for each variable. Data on financial literacy is available only in the last (2017) wave of the NIDS survey.

The pooled data indicates that about 16% of the sample of respondents are unemployed, while the remaining are either economically inactive (43%) or employed (41%). The average monthly earning of those who are employed, as presented in Column (2), is about 4,044 South African Rand (this is about 494 USD based on an average official exchange rate of 8.19 Rand per USD in the panel survey year of 2012). There is more than one-fold variation in earnings both between and within individuals over time. There is consistently high growth in the annual earnings over time (see Figure 2), with average monthly earnings in the most recent wave outweighing the base year by about 83%. There is also a very clear and growing difference in the average monthly earnings by education categories (see Appendix Table A.1). The variation in earnings within each education group is larger than the average value by more than one-fold. In addition, the variation in wage earnings increases by education level.

The demographic information from the aggregate data, presented in Table 1 also shows that the average age of the respondents is about 34 years with the majority of them being female (58%), single (61%), and African (82%). Among the variables considered to capture the mechanisms through which early life shock might contribute to labour market outcomes later in life, average years of schooling is about 10 years; perceived health evaluated in a 1 to 5 scale is on average 3.83 and emotional well-being disorder based on the Center for Epidemiologic Studies Depression Scale (CES-D 10) is 6.95. About 33% of the respondents have elementary occupations, while the average financial literacy score is 2.14 out of 5.

Figure 1: Earnings differences by shock types

Notes: Panel (a) relates the average monthly earnings and loss of a biological father, while Panel (b) considers the loss of a biological mother.

Figure 1(a, b) presents the difference in total monthly earnings by shock experience. As shown in Figure 1(a) and Figure 1(b), there is a statistically significant difference in the mean earnings between those who have lost their biological father and mother early in their lives and those who did not, respectively. In both cases of loss of biological father and mother, the average monthly wage earnings are lower among those who have experienced the shock. The age cohort analysis (see Appendix Table A.2) reveals an interesting result where the average monthly wage-earning difference between the two groups increases statistically and economically with age. It is, therefore, imperative to expect an association between the loss of biological parents and labour market outcomes.

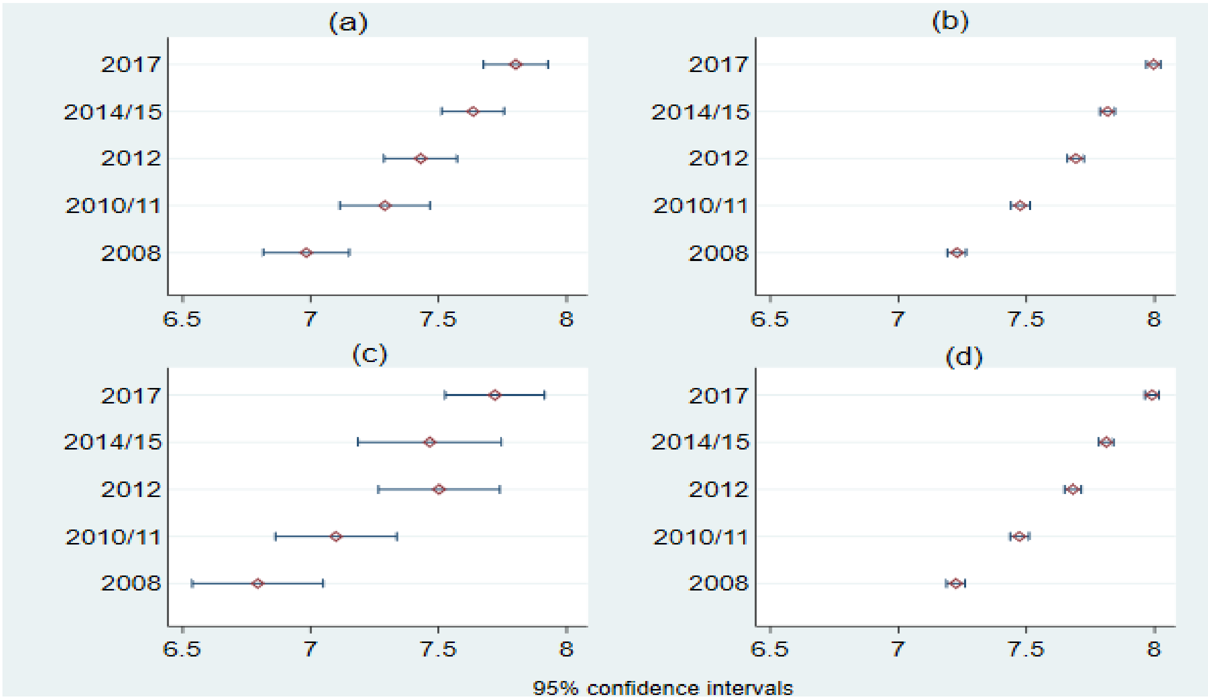

Figure 2: Earnings Variation (in Log) by Waves and Shock Types

Notes: The figure shows trends in average monthly earnings (in log) across the waves. Panels (a) and (c) are the trends for the groups who have lost their father and their mother in childhood, respectively. Panels (b) and (d) are the trends for those who have not lost their parents.

Variation in monthly total earnings by wave and shock type is also presented in Figure 2(a – d). The figure depicts first, the average earnings of those who have lost either their father or mother (as presented in Figure 2(a) and Figure 2(c), respectively) is lower in each wave compared to the control groups (presented in Figure 2(b) and Figure 2(d)). Second, there is no statistically significant difference in the earnings of those who have lost their parents across the consecutive waves, while there is a statistically significant difference in earnings growth between those who have not experienced the shocks. With this background information, we now try to explore the effect of the shock variables on the stated labour market outcomes.

5.2. Main Findings

Table 2 presents alternative estimation results of the effect of the loss of biological parents in childhood on labour market outcomes later in life. All the estimations include other control variables such as age, age squared, gender, marital status, race, and province. In these estimations cluster standard error using district municipality is used. Column (1) reports estimations results using a pooled cross-sectional ordinary least square model. The estimation result reveals that both the death of the biological father and the death of the biological mother in early life have a statistically significant association with the total monthly earnings of the respondents during adulthood. To utilize the panel structure of the data, with time-invariant regressors of the variables of interest, a random effects model is estimated and presented in Column (2). Like the first estimation, both shocks have statistically significant associations with wage earnings. The random effects model has weakness in terms of controlling time-invariant unobserved heterogeneities, while the fixed effect solves the problem at the expense of dropping the coefficients of time-invariant regressors. As a result, a CRE model proposed by Mundlak (1978) and Chamberlain (1980, 1982) is used to account for the fixed effect of time-varying covariates while keeping the estimates of time-constant variables.

Column (3) presents the estimation results from the CRE model, where the deaths of the biological father and mother are statistically significant in explaining wage earning variations. The earnings figure of those who have lost their father is lower by about 13.3% than for those who have not experienced the shock. Consistently, the earnings amount of those who have lost their biological mother during childhood is lower on average by about 22% than for those who have not lost their mother. Previous studies that explored the effect of early life shock on late life economic outcomes show consistent results, but with a lower magnitude. For instance, Isen et al. (2017) show a 0.1% reduction in adult annual earnings due to an extra day with mean temperatures above 32°C in utero, while Tien and Adoho (2018) found a 2.5 to 3.5% difference in overall inequality of adulthood earnings due to early adulthood (ages 18-25) exposure to intensely violent conflict. According to Beegle et al. (2010), maternal orphanhood leads to 8.5% lower consumption expenditure during adulthood. In this and prior estimations, the impact of the death of a mother in early life is higher in magnitude than that of the death of a father. This could be due to the greater role mothers play in the human capital formation of their children.

Gender roles and differences have always been a point of discussion with varying evidences across countries. Though there is progress in gender equality as labour force participation of women and mothers is growing (V. Gay et al., 2018; Neilson & Stanfors, 2014), the contribution of women in housework and childcare is still greater than the contribution of men, particularly in developing countries (Bird, 1999; Forste & Fox, 2012). Such variation arises due to differences in individual-level variables such as relative resources, time availability, and gender ideology. In addition, macro factors such as economic development, female labour-force participation, gender norms, welfare regimes (Fuwa, 2004), and cultural difference (V. Gay et al., 2018) among others, explain gender gaps. On top of the greater responsibility that women bear concerning housework and childcare, resources controlled by women are mostly geared towards increased household expenditures on inputs into child well-being, including nutrition, education, and health services (Haddad et al., 1997; Hopkins et al., 1994; Menon et al., 2014; Richards et al., 2013). The evidence that the loss of a mother harms human capital and thereby labour market outcomes in the later life of children is a clear indication of the contribution of women in the human capital development of their children.

Table 2: The Effect of Early Life Parental Death on Earnings and Unemployment

	(1) POLSEar	(2) REEar	(3) CREEar	(4) HeckEar	(5) ProbUnem
Panel A - Earnings (in log)					*Unemp.*
Death of a Father	-0.136**	-0.155**	-0.133**	-0.153***	0.072*
	(0.050)	(0.048)	(0.044)	(0.046)	(0.034)
Death of a Mother	-0.206**	-0.216***	-0.219**	-0.221***	-0.151*
	(0.075)	(0.064)	(0.073)	(0.058)	(0.061)
Panel B - Employed Dummy					
Father				-0.229***	
				(0.053)	
Mother				-0.414***	
				(0.078)	
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Municipality Fixed Effects	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes
Observations	24472	24472	24472	62915	62915

Notes: Alternative earning estimation results are provided in Columns (1) to (4), while a Panel Probit estimation for the unemployed dummy is given in Column (5). Column (1) and Column (2) report estimation results from pooled ordinary least square and random effect models, respectively. In these estimations, cluster standard error using district municipality is used. Column (3) presents the estimation of the main model, a Correlated Random Effect model. A Heckman selection model is depicted in Column (4), where the result from the Probit estimation of the Heckman model is given in Panel B. Control variables used in the estimations, other than indicated, include age, age squared, gender, marital status, and race. For estimations in Columns (3) to (5) robust standard errors are used once the district municipality replaces the province as control. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In our earnings equation, we consider respondents who receive wage earnings from employment (including self-employment). However, the experience of shocks in early childhood that affect human capital might deter working-age respondents from labour market participation. If that is the case, the estimations run earlier may suffer from the problem of sample selection. To account for this, Heckman (1979) suggests a two-step estimation. Accordingly, the first model estimates the probability of participation in the labour market using Probit regression, while the second model estimates the earning equation, considering the result of the former estimates. Identification in the Heckman model requires a valid exclusion restriction in the selection equation, where the excluded variable needs to affect selection but not the outcome. Different studies used different variables to satisfy the exclusion restriction criteria. In this study, household size was included in the selection equation but excluded from the earning equation. The justification for the use of this variable is that it might affect the likelihood of employment participation, but an individual's earning level is unlikely to depend on family size. In addition, different studies used the number or presence of children, which is highly correlated with family size, in the selection equation to satisfy the exclusion restriction (Chi & Li, 2014; Hoffmann & Kassouf, 2005; Zheng et al., 2018). Considering the lack of tests for the validity of the instrument used and possible concerns about the justification, the study is limited to describing associations without making causal inferences.

Column (4) of Table 2 presents the estimation results based on Heckman selection approach using household size as an additional control in the selection equation. The results are consistent with all the above alternative estimations. In the Probit estimation of the Heckman model, the death of a father and the death of a mother both have a statistically significant adverse effect on the probability of working. Those who have lost their biological mother in childhood have about 41% lower probability of being employed than their counterparts. Similarly, the difference is about 23% in the case of the death of a biological father.

We also estimate the probability of being unemployed as a function of the shock variables and other controls using a panel Probit model and report the results in Column (5) of the same table. The results suggest that those who lost their father have a higher probability of being unemployed, while those who lost their mother have a lower probability compared to their respective counterparts. Combining this result with the Probit estimation from the Heckman estimator shows that those who have lost their mother have a lower probability of being both employed and unemployed. This implies that the loss of a mother seems to put the majority in the economically inactive category compared to their counterparts. This could be due to the lower likelihood of those who have lost their mother being in a good position in terms of their human capital status (Beegle et al., 2010). However, for those who have lost their father, while the probability of being employed is lower, the likelihood of being unemployed is higher. This means they are striving to find a job but with a lower probability of obtaining employment. This could be due to the two-sided effect of the loss of a biological father in early life. First, higher tendency for the household to experience income shock following the loss of a father, as in most cases the relative household income share of husbands is higher (Bertrand et al., 2015). This is more likely true (with a higher share) in developing countries, particularly in a society where males are considered the main breadwinner. Second, children have a higher chance of human capital development if the surviving parent is a mother as a mother's contribution to parenting is usually greater. In these contradictory situations, children with some human capital are forced to enter the labour market earlier to support the household economically though they have a lower tendency to obtain employment.

In the discussions so far, the effects of the death of a biological father and the death of a biological mother were analysed independently to see how they relate to later earnings. Nevertheless, the interaction term between the death of a father and the death of a mother which captures the effect of the loss of both biological parents is found to be statistically insignificant. This could be due to a sample size problem as the proportion of those who have lost both of their biological parents in early childhood accounts for less than 0.5% of the total observation. The other reason could be due to interventions, like foster child grants or orphanhood projects in

South Africa, which are intended to protect only children who have lost both of their biological parents in their childhood.

Table 3: Early life Parental Death and Earnings - Heterogeneity Analysis

	(1) FathGender	(2) MothGender	(3) FathRace	(4) MothRace
Death of a Father*Female	-0.096			
	(0.087)			
Death of a Mother*Female		-0.277†		
		(0.150)		
Death of a Father*African			0.297*	
			(0.123)	
Death of a Mother*African				0.153
				(0.157)
Death of a Father	-0.079	-0.132**	-0.376***	-0.133**
	(0.060)	(0.044)	(0.114)	(0.044)
Death of a Mother	-0.216**	-0.039	-0.215**	-0.334*
	(0.073)	(0.120)	(0.073)	(0.131)
Female	-0.361***	-0.362***	-0.366***	-0.366***
	(0.019)	(0.019)	(0.019)	(0.019)
African	-0.543***	-0.543***	-0.554***	-0.545***
	(0.035)	(0.035)	(0.035)	(0.035)
Time Fixed Effects	Yes	Yes	Yes	Yes
Municipality Fixed Effects	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Observations	24472	24472	24472	24472

Notes: Column (1) and Column (2) report CRE estimation results once the interaction term between the death of a father and the death of a mother is incorporated with the gender of the respondent (female dummy). In the same way, Column (3) and Column (4) introduce the interaction term of the respective shock variables with the race of the respondents (black South African dummy). Other control variables used in the estimations are age, age squared, gender, marital status, and race. Robust standard errors are given in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

It is also worth investigating whether the effect of such shocks varies across socio-demographic factors. In line with this, heterogeneity analyses using gender and race are estimated and presented in Table 3. Columns (1) and (2) report the interaction between the shock variables and gender to check if there is variations in the effect of the shocks on wage earnings between male and female respondents. As discussed earlier, for multifaceted reasons women bear more burden at home than men, particularly in developing countries, and we, therefore, expect the effect of the shock to varying by gender. The heterogeneity analysis using a Correlated Random Effect model reveals no statistically significant difference in the effect of the shock by gender. Only at the margin (10% level of significance) do women who have lost their mothers in childhood earn lower wages than men who have lost their mothers in childhood.

Racial discrimination is an important legacy of apartheid in South Africa which was in place until 1994. Though anti-discrimination legislation has been in place since then, racism and its manifestations remain an issue in the country (Pillay, 2014; Slabbert, 2001). Discriminatory actions due to racism are expected to have psychological, social, political, and economic consequences. For instance, Oliver et al. (2006) indicate a clear difference in earnings and wealth between black and white South Africans. The results from the main estimation in this study are consistent with the literature, where the earnings of the majority of Black South Africans are lower on average by about 54% than the other race categories. Here it is also interesting to see the existence of a difference in the effect of the shocks between race categories, with the assumption that Black South Africans are discriminated against social and economic insurances (formal or informal) following the loss of their biological parents. The interaction term between the death of a biological father and a black South African dummy reveals a result contrary to our expectation. Black South Africans who lost their father during childhood earn higher wages than those in other race categories who have experienced the same shock. On average, Black South Africans who have lost their father earn a wage higher by about 30% than the other race groups who have lost their biological father too. Though thorough and further investigations are required, one of the reasons could be the opportunity provided by the Expanded Public Works Programme (EPWP) and other government job creation programmes in South Africa. The EPWP, for instance, aims to provide short- to medium-term employment opportunities and income transfers to poor households. With this in mind, about 90% of the beneficiaries of the South African EPWP and other government job creation programmes are black South Africans (Statistics South Africa, 2020). Therefore, this might have provided a better opportunity for those black South Africans who have experienced paternal death and are economically deprived than the other race groups who have experienced the same shock.

5.3. Robustness Checks

The previous estimations considered shocks experienced by respondents before their fifth birthday. The results presented in Column (1) of Table 4 are from the shock experienced before the respondents were formally eligible to participate in the labour market, to check for consistency of the results. For this, whether respondents lost their biological mother and father before age 15 is used as the main independent variables. As the estimation result reveals, both the death of a biological father and mother are statistically significant in explaining wage differences, though the magnitude of the effect is lower than if the shock is experienced before the age of 5. The death of a biological father results in an average wage that is lower by about 7%, while the death of a mother results in lower wage earnings of about 16%. In general, consistent with the results of the main estimation, the loss of biological parents has a detrimental effect on labour market outcomes, where the effect of the loss of a biological mother is higher than the effect of the loss of a biological father.

There are concerns related to the consistency and validity of the results from the above estimations. One of the main concerns is whether the results are attributed to idiosyncratic shocks, which might be confounded with covariate shocks. To disentangle the effect of idiosyncratic shocks from covariate shocks, an interaction term between respondents' year of birth and place of birth is introduced as a means to control the effect of covariate shocks, with the assumption that no mobility of parents occurred before the child was 5 years old. These variables are considered good proxies for the year and place of death of the parents, respectively. Column (2) presents estimation results once the interaction term is introduced as an additional control into the Correlated Random Effect model with robust standard error. The result is still consistent with estimations from the main model, where both the death of a biological father and mother are statistically significant in explaining earnings variations. The magnitude of the effect is also similar to the coefficients from the main estimation model.

Table 4: Robustness Checks

	(1) DBef15	(2) CovShock	(3) Attrit	(4) HTaylor
Death of a Father	-0.070**	-0.131**	-0.133**	-4.760**
	(0.025)	(0.044)	(0.044)	(1.507)
Death of a Mother	-0.164***	-0.222**	-0.219**	-8.325**
	(0.040)	(0.073)	(0.073)	(2.944)
Wave freq.			0.009	
			(0.041)	
Time Fixed Effects	Yes	Yes	Yes	Yes
Municipality Fixed Effects	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Observations	24338	24472	24472	24472

Notes: Column (1) presents CRE estimation of the effect of the death of a biological father and the death of a biological mother before the age of 15 on wage earnings. Column (2) reports CRE estimation results once the interaction term between the place of birth and year of birth is introduced as an additional explanatory variable. This helps to disentangle idiosyncratic shocks from covariate shocks. Column (3) shows a test for attrition bias based on the main estimation model. Column (4) presents the Hausman-Taylor estimator. Other control variables used in the estimations are age, age squared, gender, marital status, and race. Robust standard errors are given in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The second aspect to be checked to confirm the reliability of estimation results in a panel data setup is attrition bias. This study considers unbalanced panel data with observations in at least two waves. As described in Section 4.1, the attrition rate from wave 1 to wave 5 is 27%. Thus, attrition might bias the estimation results. To check this, Wooldridge (2010) suggests the inclusion of lead or lag of the selection (time) variable or the number of subsequent waves observed in the dataset to test their significance. To preserve the number of observations used in the main estimation, the number of waves is introduced as an additional explanatory variable.

The estimation result presented in Column (3) of the table reveals that the introduced variable is statistically insignificant. Therefore, the estimation result from the main model is not subjected to attrition bias and is reliable.

The third and most important concern for causal interpretation is the randomness of the shock variables. Acknowledging the non-random nature of the shock variables, alternative estimations and hypotheses are tested to validate the results. The main estimation model in this study, the correlated random effects model, has the advantage of providing effect estimates of time-invariant variables that are unbiased by a possible correlation with time-varying unobserved heterogeneity. However, this is based on a strong assumption that the time-invariant variable is uncorrelated with time-invariant unobserved heterogeneity. That is, the main time-invariant independent variable is assumed exogenous (Schunck, 2013). In this case, an approach proposed by Hausman and Taylor (1981) provides an internal instrument to consistently estimate the coefficient of time-invariant endogenous variables, the shock variables in this study. This approach also requires that the instruments should be uncorrelated with individual effects and the idiosyncratic error terms. The estimation result, presented in Column (4), is still consistent in terms of sign and significance, though we have inflated coefficients and standard deviations. This is due to the weak instruments that cause serious size distortions. For instance, the inclusion of parents' education in the model removes about half of the size distortion.

To check for an alternative hypothesis which could explain the death of biological parents and at the same time earnings are tested and presented in Table 5. Random effects models are run for comparison, with the simple random effect model presented in Column (1). The first question could be "What if the death of biological parents was due to hereditary diseases which transmit to their offspring and make them economically less active?". If the early age death of parents is due to hereditary diseases, we also expect that to happen to their children or at least would make their children economically inactive earlier than others and exit the labour market. There is some evidence documenting a lower life expectancy for those who suffer from hereditary diseases (Kang et al., 2017; Wilding et al., 2012). On the other hand, data from the World Bank indicates that the average life expectancy at birth in South Africa for the period between 1960 and 2005 was about 56.5 years. We, therefore, expect the wage differential to die out with the increasing age categories, particularly for the age category above 45 years. The result presented in Table 5 in Columns (2) to (4), however, is contrary to our expectations statistically and economically. It implies that shocks experienced in early childhood have a persistent and growing effect on labour market outcomes. Contrary to our argument, if the hereditary disease makes the victims less productive while they stay participating in the labour market could lead to a higher wage differential.

The second question we ask is "What if the economic status of parents is the reason for their death and could also contribute to the nature of the later wage earnings of their children through human capital investment or bequests?". If that is the case, we expect introducing the income level of parents into the earnings equation in addition to the shock variables to erode the effect of the latter. To empirically check this, the income of parents at the age the respondents were qualified to enter the labour market is considered due to the lack of data on income at the early age of the respondents and the regression results are presented in Column (5) of Table 5. The result reveals marginal difference in the effect of the shock variables compared with the estimation in Column (1), which invalidates our hypothesis. The other hypothesis is the role of the occupation type of parents in determining the wage earnings of their children. What if the occupation type of the parents is the reason for their death and their children's subsequent earnings, given there is a high possibility that children will follow the occupation type of their parents? Here as well, we expect the effect of the shock variables to drop at least in magnitude once the occupation type of parents is controlled for. The result as presented in Column (6), however, doesn't meet this expectation consistently.

Table 5: Early Life Parental Death and Earnings - Sensitivity Analysis

	(1) Simple	(2) A15-30	(3) A30-45	(4) A45+	(5) Inc	(6) POcc	(7) FBA5	(8) MBA5
D. Father	-0.218***	-0.079	-0.186**	-0.342***	-0.203***	-0.299***	-0.143*	
	(0.053)	(0.091)	(0.060)	(0.094)	(0.051)	(0.061)	(0.067)	
D. Mother	-0.366***	-0.296**	-0.233	-0.500***	-0.347***	-0.294**		-0.234**
	(0.079)	(0.109)	(0.122)	(0.149)	(0.078)	(0.110)		(0.086)
Controls	No	No	No	No	Yes	Yes	No	No
Obs.	24472	7357	9896	7219	23850	12547	3852	1448

Notes: Column (1) reports a base model which estimates the effect of idiosyncratic shock variables (death of father and death of mother before age of 5) on monthly wage earnings. Columns (2) to (4) decompose the prior estimation by age category to check if the effect of the shock variables is vanishing with age. Columns (5) and (6) control the effects of the income step of parents at the 15th age of the respondent and occupation category of parents, respectively. Columns (7) and (8) compare the effects of the loss of parents before age of 5 with the loss of parents between the ages of 5 and 15. Due to the time-invariant nature of the independent variables in these estimations random effects model is used with clustered standard errors (given in parentheses). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Finally, one of the other options to check for the importance of loss of biological parents early in life in determining late-life labour market outcome is to compare groups who have experienced the shock before the age of 5 and after the age of 5 (but before the age of 15). In this scenario, it is hard to argue that the death of parents before the respondents' 5th birthday has unique characteristics compared to parental death after the child's 5th birthday. A comparative analysis presented in the last two columns of the table shows that the effect of early childhood shock (before age of 5) is statistically significant in explaining variation in wage earnings in comparison to shocks experienced in middle and late childhood (age between 5 and 15 years). The effect of the loss of a mother in early childhood is both economically and statistically higher than the loss of a father. In general, accounting for possible sources of endogeneity to check for consistency of the results, the loss of biological parents early in life has a significant effect on later labour market outcomes.

5.4. Mechanisms

There is ample literature supporting a strong association between human capital and labour market outcomes. Positive labour market outcomes are highly likely to occur whenever there is a high investment in human capital early in life. On the other hand, shocks which hamper investment in children are expected to lower their labour market outcomes. Accordingly, in the above analysis, we document the adverse relationship between idiosyncratic shocks and labour market outcomes. The main channel, as described above, is expected to happen through human capital development. Given this, we consider education attainment, perceived health, emotional well-being disorder and cognitive ability as the main possible channels through which shocks affect labour market outcomes. In addition, the occupation type of respondents is also checked as a possible mechanism.

Table 6: Mechanisms - Employed Sample

	(1) Education	(2) PHealth	(3) EmoWellbeing	(4) OccuElemd	(5) FinLitw 5
Death of a Father	-0.493**	-0.012	0.039	0.103	-0.049
	(0.154)	(0.033)	(0.127)	(0.099)	(0.064)
Death of a Mother	-1.186***	-0.160**	0.290	0.489**	-0.394***
	(0.273)	(0.060)	(0.234)	(0.181)	(0.113)
Time Fixed Effects	Yes	Yes	Yes	Yes	No
Municipality Fixed Effects	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes
Observations	24416	24429	23896	23632	5786

Notes: Columns (1) to Column (3) report CRE estimation results with education level, perceived health, and emotional well-being disorder as outcome variables, respectively. Column (4) shows panel Probit estimation using an elementary occupation dummy as a dependent variable. Column (5) presents the OLS estimation of financial literacy as an outcome which is available only in wave 5. Other control variables used in the estimations are age, age squared, gender, marital status, and race. Robust standard errors are given in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6 reports estimations based on alternative outcome variables only for respondents with positive wage earnings (employed sample). The first three estimations are based on the correlated random effect model with outcome variables of education level (measured in years of schooling), perceived health (measured in the range of 1 (very low) to 5 (very high)), and emotional well-being disorder (measured using the Center for Epidemiologic Studies Depression Scale (CES-D 10)), respectively. Column (4) presents regression results from a panel probit estimator considering an elementary occupation dummy as an outcome variable. Lastly, information on financial literacy (measured in the range of 1 (very low) to 5 (very high)) becomes available in the fifth wave of NIDS data, and OLS estimation is used on this variable, and the results are presented in column (5) of the table. In this estimation, financial literacy is used as a proxy for cognitive ability, as supported by literature that documented the existence of a strong association between financial literacy and cognitive ability (Banks, 2010; Gaurav & Singh, 2012).

Column (1) presents education level as one of the main mechanisms to link the loss of parents in early life with labour market outcomes. As the result reveals, education level is negatively associated with the death of both biological father and mother. The education level of those who have lost their father in childhood is lower by about 0.5 than those who have not lost their father. The difference for those who have lost their mother is more than twofold higher than for those who have lost their father. That is, the educational attainment of those who have lost their mother is about 1.2 years lower than those who have not lost their mother. This figure accounts for about 12% of the average education level of all the respondents in the sample. This implies the contribution of surviving mothers to the education of their children. Consistently, the contribution of mothers in maintaining and improving their children's health is paramount. In support of this, as given in Column (2) of the table, only the death of a mother is statistically significant in explaining differences in perceived health among the respondents. In line with these, cognitive ability, proxied by financial literacy, is explained again only by the death of a mother (see Column 5). However, the death of a father or the death of a mother is found to be statistically insignificant in determining emotional well-being disorder. In this study, emotional well-being disorder is measured by the Center for Epidemiologic Studies Depression Scale (CES-D 10) developed by Radloff (1977), which is one of the most commonly used measures of mental health disorder. A consistent result is obtained by considering if the shock (death of parents) happened before the age of 15 rather than before 5 years of age (see Appendix Table A.3).

Individuals in the labour force with lower levels of human capital are expected to have less chance of getting employment. If they do secure employment, they have a higher probability of being employed in elementary occupations than as professionals. Therefore, if the death of biological parents adversely affects the human capital development of the victims, they are more likely to be employed in elementary jobs. The result presented in column (4) of the table is partly in support of this hypothesis where those who have lost their mother have a high probability of having an elementary occupation, while the result is insignificant for the death of a father. It is also important to note that the loss of biological parents might completely lock the victims into economically inactive or unemployed groups. It is, therefore. worth checking the validity of the mechanisms for all sample respondents.

Table 7: Mechanisms - All Sample

	(1) Education	(2) PHealth	(3) Emowellbeing	(4) FinLitw5
Death of a Father	-0.403***	-0.032	0.116	-0.025
	(0.109)	(0.021)	(0.080)	(0.042)
Death of a Mother	-0.975***	-0.117***	0.278*	-0.245***
	(0.192)	(0.035)	(0.122)	(0.071)
Time Fixed Effect	Yes	Yes	Yes	No
Municipality Fixed Effect	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Observations	62782	62826	61611	12645

Notes: Estimations in this table account for all sample respondents including those without a job (earnings). Columns (1) to (3) report CRE estimation results with education level, perceived health, and emotional well-being disorder as outcome variables, respectively. Column (4) presents an OLS estimation of financial literacy as an outcome as data on financial literacy become available in wave 5. Other control variables used in the estimations are age, age squared, gender, marital status, and race. Robust standard errors are given in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All sample respondents are considered in checks for consistency of the mechanisms, as presented in Table 7. The results are robust to what we have presented in Table 6 except that in the current estimation death of a mother is statistically significant in explaining emotional well-being disorder. That is, those who have lost their mother have higher rates of emotional well-being disorder than their counterparts. Overall, the death of a father and the death of a mother are both found to be statistically significant explanation for labour market outcomes, though the magnitude of the effect is higher for the loss of a biological mother in early childhood. Consistently, the death of a mother is statistically and economically significant in explaining variation in the channels, while education level is the only channel among the alternatives that links the loss of a father with wage earnings. Therefore, due attention should be given to those children who have lost their parents, with more emphasis on those who have lost their mother in early life, to minimize the adverse effect on their future livelihoods as it is likely to affect the livelihood of the succeeding generation and the economy of the country (Alam, 2015; Andersen, 2013; Bratti & Mendola, 2014; Lindo, 2011).

6. Conclusion

Previous literature on early-life shocks and late-life outcomes concentrates on relating covariate shocks such as rainfall variability, price volatility, war, and famine to health and education-related outcomes that include health status, education attainment, psychological or mental well-being, and cognitive ability. Rigorous studies exploring the effect of early life idiosyncratic shocks on labour market outcomes are rare, particularly in a developing country context. In this paper, we estimate the impact of early life idiosyncratic shocks on labour market outcomes. This paper extends the literature in two ways. First, idiosyncratic shocks which are specific to households are considered the main independent variables. Second, labour market outcomes are taken as outcome variables.

The key idiosyncratic shocks we consider are the death of a biological father and of a biological mother before the age of five. The main labour market outcome variable considered is monthly wage earnings, while unemployment is also used as an alternative indicator. The estimations used five waves of panel data from the National Income Dynamics Study (NIDS) (2008 - 2017) with a total observation of close to 63,000. We found that the mean difference in monthly wage earnings between those who lost their parents in childhood and those who did not is statistically significant. Consistently, while there is no statistically significant difference in the average wage earnings over time for those who experienced the shocks, there is statistically significant growth for those who did not experience the shocks.

Alternative estimations reveal that both the death of a biological father and the death of a biological mother in early childhood adversely affect wage earnings during adulthood, though the magnitude of the effect of the death of a mother is consistently higher than the death of a father. Results from heterogeneity analysis show that Black South Africans who lost their father in childhood earn higher wages than the other race categories that experienced the same shock. Associating the shock variables with unemployment indicates that the death of a mother is negatively related to both the probability of being unemployed and the probability of working which implies a positive association with the economically inactive category. However, the death of a father is negatively associated with the probability of working but positively associated with the probability of being unemployed. The main mechanisms through which the death of a mother affects wage earnings are education level, perceived health, cognitive ability, and higher probability of being employed in an elementary occupation. The adverse effect of the death of a father is mainly channelled through lowering education levels.

6.1. Policy Implications

The results of this study clearly demonstrate the need for strengthening and aligning child support programmes to meet their intended goals. In South Africa, there is a child support programme, the foster child grant, that targets children who have lost both of their parents. This programme needs to target children who have lost either of their parents, particularly those who have lost their mother and are financially needy. The programme should also go beyond the financial grant to monitor its implementation in helping children in terms of their human capital formation. Psychological support for children should also be considered. The estimation results also imply that informal insurance, which is expected to minimize the impact of idiosyncratic shocks, does not function well to solve the problem. Therefore, it is also worth considering making households and the communities aware of the issue so that informal social protection plays a part in reducing the adverse consequences for children.

6.2. Limitations and further study directions

In analyzing the effect of early-life parental death on labour market outcomes, this study is limited to exploring and explaining associations rather than drawing causal interpretations. Causal interpretation necessitates a clear identification, where parental death should be either exogenous or at least be instrumented by exogenous variables. In the heterogeneity analysis, black South Africans who lost their biological father early in life are found to earn higher wages than the other race groups who have experienced the same shock. The study is constrained in its ability to investigate the reasons why. Therefore, future studies are likely to fill these gaps.

Data availability

The raw data is publicly available at the Datafirst's website. Data and codes to replicate all the results will be available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Gidisa Lachisa Tato: Conceptualization, Methodology, Data curation, Formal analysis, Writing - original draft, Writing - review & editing. **Assefa Admassie:** Conceptualization, Writing - original draft, Writing - review & editing, Supervision.

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A. Appendix - Additional Tables

Table A.1: Earning Variation by Education Categories

	(1) Mean	(2) Std. dev.	(3) Freq.
No formal education	1392.06	1475.48	1225
Primary education	1647.50	2107.00	2659
Secondary education	3075.31	5470.48	15708
Post-secondary education	9133.07	12678.75	4880
Total	4043.90	7654.60	24472

Notes: Column (1) shows the monthly wage earnings of the pooled data by education category. Column (2) presents the standard deviation of monthly earnings by the respective education categories, followed by Column (3) depicting the number of observations in each educational attainment category.

Table A.2: Mean Difference Tests by Shock Types and Age Groups

	(1) Age15-29	(2) Age30-44	(3) Age45+
Monthly Wage Earnings (in log) (Father Deceased)	0.073	0.143^{**}	0.404^{***}
	(1.16)	(2.72)	(6.45)
Monthly Wage Earnings (in log) (Mother Deceased)	0.291^{*}	0.233^{*}	0.503^{***}
	(2.40)	(2.30)	(4.86)
Observations	28981	17319	16615

Notes: The table provides mean difference tests for monthly wage-earning differences by age cohort. Column (1) is the result for the first working age group (age 15 to 29), while Columns (2) and (3) report mean difference tests for age groups 30 to 44 years, and 45 and older, respectively. t statistics are given in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3: Mechanisms - Employed Sample and Parental Death before Age of 15

	(1) Education	(2) PHealth	(3) Emowellbeing	(4) OccuElemd	(5) FinLitw5
Death of a Father	-0.172*	-0.027	0.128	0.100	0.025
	(0.087)	(0.020)	(0.079)	(0.059)	(0.037)
Death of a Mother	-0.658***	-0.063*	0.219	0.229*	-0.180***
	(0.125)	(0.029)	(0.124)	(0.090)	(0.054)
Time Fixed Effect	Yes	Yes	Yes	Yes	No
Municipality Fixed Effect	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes
Observations	24282	24295	23764	23500	5764

Notes: Columns (1) to (3) report CRE estimation results with education level, perceived health and emotional well-being disorder as outcome variables, respectively. Column (4) shows the panel Probit estimation using an elementary occupation dummy as a dependent variable. Column (5) presents the OLS estimation of financial literacy as an outcome as financial literacy data becomes available in wave 5. Other control variables used in the estimations are age, age squared, gender, marital status, and race. Robust standard errors are given in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter Four

The Dynamic Impact of Parental Death on Child Labour: Panel Data Evidence from Ethiopia

Gidisa Lachisa Tato[1]

Abstract

This paper provides the first systematic study of the dynamic impact of parental death on child labour. Using conditional staggered difference-in-differences on rich panel data from Ethiopia, I show that parental death has a statistically significant impact on child labour. I document four key results. First, the cumulative effect of parental death outweighs the immediate effect. Second, the impact of parental death is greater around the age of 12 than earlier or later in life. Third, when a parent dies, children are forced to undertake unpaid household tasks rather than engage in economic activity. Finally, the death of a mother affects child labour more than the death of a father. The findings imply the clear need for context-specific policy interventions and long-term support initiatives to reduce the negative impact of orphanhood on child development.

JEL: I12, J22, J26, K31, O15

Keywords: Parental death, child labour, dynamic, staggered diff-in-diff, Ethiopia

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1. Introduction

Natural and man-made events have historically increased orphanhood. The HIV/AIDS pandemic was the primary cause of orphanhood in the late 1990s and early 2000s, with the highest prevalence in Sub-Saharan Africa (Beegle et al., 2006a; Case and Ardington, 2006; Evans and Miguel, 2007). Similarly, the COVID-19 epidemic resulted in an estimated 10.5 million children worldwide losing their parents and caregivers in 2019 alone (Hillis et al., 2022). Researchers and policymakers were drawn to such incidents in order to investigate their implications. The literature shows that, regardless of the causes, the impact of orphanhood on child development is extensive. The majority of these studies investigate the impact of orphanhood on educational outcomes (Ainsworth et al., 2005; Ainsworth and Filmer, 2006; Ardington and Leibbrandt, 2010; Beegle et al., 2006a; Case and Ardington, 2006; Case et al., 2004; Cas et al., 2014; De Vreyer and Nilsson, 2019; Evans and Miguel, 2007; Gertler et al., 2004; Kazeem and Jensen, 2017; Senne, 2014). However, the impact of orphanhood on child labour has received less attention.

This paper examines the dynamic impact of parental death on child labour using five waves of rich panel data from Ethiopia - the Ethiopian Young Lives longitudinal data obtained from the UK data Service. I use the staggered difference-in-differences with multiple periods of treatment estimator to identify the impact of parental death on child labour in Ethiopia. The approach allows the study to account for time-invariant unobserved heterogeneity between orphans and non-orphans. The estimates are conditioned on pre-orphanhood individual and household characteristics to check for parallel trends between orphans and non-orphans. Regression results suggest that, in Ethiopia, parental death increases child labour considerably. Children who have lost one or both of their biological parents are more likely to be involved in child labor. Specific estimations also reveal four key findings. First, the cumulative effect of orphanhood is greater than the immediate effect. Thus, children who lose their parents while they are young (between the ages of 6 and 8 years) are more affected than children orphaned at later ages. Second, the impact of parental death on child labour is greater around the age of 12 than sooner or later in life. Third, parental death causes children to undertake unpaid household tasks (care and domestic tasks) rather than engage in economic activities (farm activities, participation in family businesses, and paid work). Finally, the death of a mother has a bigger effect on uptake of child labour than the loss of a father. Changes in living situations are also related to orphanhood. Single-orphaned children are more likely to live outside of a household where the surviving biological parent is the household head or child-carer.

This paper contributes to the development economics literature on orphanhood and child development in several ways. The literature on this topic is focused largely on investigating the impact of parental mortality on childrens' education. There is evidence that parental death has a negative impact on children's school enrolment and achievement (Beegle et al., 2006a; Case and Ardington, 2006; Case et al., 2004; Cas et al., 2014; Evans and Miguel, 2007; Gertler et al., 2004; Senne, 2014). Other research, on the other hand, reveals little or no evidence of a decline in the educational outcomes of orphans compared to non-orphans (Ainsworth and Filmer, 2006; Ardington and Leibbrandt, 2010; Lloyd and Blanc, 1996; Ainsworth et al., 2005). Though there is a large body of literature on the relationship between orphanhood and child schooling, empirical evidence on the relationship between orphanhood and child labour is scarce (Kamei, 2018; Novella, 2018). This study therefore contributes to the literature on orphanhood by analysing its impact on child labour.

The mixed evidence on the impact of parental death on child outcomes are attributed to several of factors. The role of extended families and social networks has been shown to reverse the potentially negative effects (Case et al., 2004; Kazeem and Jensen, 2017; Novella, 2018; Beegle et al., 2010; De Vreyer and Nilsson, 2019; Ardington and Leibbrandt, 2010; Parker and Short, 2009). An alternative explanation for the contradictory results is a discrepancy in the time of parental deaths. Himaz (2013), for example, has found a statistically significant negative effect of parental death on child enrolment and sense of optimism when the shock occurs between ages of 7 to 12. However, the impact is non-existent when it occurs in adolescence. Similarly, there are studies that have examined the effects of differences in timing of parental illness or death on child outcomes (Dhanaraj, 2016; Case and Ardington, 2006; Brent et al., 2012). This research contributes to this strand of the literature by examining disparities related to the date of parental death and the impact of parental death over-time at different ages of the child.

This research also contributes to the literature on child labour, which is still a key concern in global development. Despite the United Nations Sustainable Development Goal (SDG) of eliminating all kinds of child labour by 2025, its prevalence remains significant, particularly in developing nations. According to the UNICEF, 160 million children (39.4% girls) were in child labour worldwide at the start of 2020, accounting for about one in every ten children. Over half of these children were involved in hazardous work that directly jeopardised their well-being. Furthermore, children in Sub-Saharan Africa are the most vulnerable to child labour, accounting for more than half of the global total (ILO and UNICEF, 2021). Such exposures have a negative effect on children's physical and mental development, as well as their future livelihoods (Ibrahim et al., 2019; Trinh, 2020; Dinku and Fielding, 2021; Dinku et al., 2019; Mussa et al., 2019; Burrone and Giannelli, 2020). As a result, developing effective measures to combat child labour requires a full understanding of the causes.

The literature cites a number of macro- and micro-level factors related to child labour. Micro or household factors include household economic well-being needs and shocks (Beegle et al., 2006b; Tanaka, 2003; Bandara et al., 2015; De Janvry et al., 2006; Dillon, 2013; Guarcello et al., 2010; Fitz and League, 2021; Soares et al., 2012), and demographic composition and structure (Alvi and Dendir, 2011; Seid and Gurmu, 2015; Edmonds, 2007). Other household-level factors that influence child labour include parental health shocks. The illness of family members, particularly parents, has been proven to increase child labour (De Janvry et al., 2006; Edmonds, 2010; Lim, 2020; Mendolia et al., 2019; Woode, 2017; Dinku et al., 2018; Dillon, 2013). On the other hand, there is also an evidence that parental illness has no effect on child labour (Alam, 2015). The impact of parental death, which is a permanent shock unlike other income and non-income shocks, on child labour, has received less attention. Kamei (2018) used a sequential logit model to indicate an increase in the chance of hazardous child labour owing to paternal death. Similarly, Novella (2018) demonstrated that orphans are more likely to engage in child labour than non-orphans. As a result, this paper contributes to the literature by investigating the dynamic impact of parental death on child labour.

By utilising panel data from Ethiopia, this study also contributes to the literature on orphanhood and child labour in developing countries. Ethiopia is an appropriate setting for investigating the relationship between orphanhood and child labour because both situations are pervasive in the country. According to the Ethiopian child labour survey conducted in 2001 52.1% of children aged 5 to 17 years were engaged in economic activities. The figure was 51% in the 2015 survey. However, the proportion of children engaging in household chores exceeds 70%. According to the ILO definition, 42.7% of children in the country are engaged in child labour (CSA, 2002; CSA and ILO, 2018). Ethiopia, also has a large orphan population. According to data from the Ethiopian Demographic and Health Surveys (DHS), roughly 10% (in 2011) and 8.2% (in 2016) of children under the age of 18 are single or double orphans. Given the scarcity of evidence in this setting, it is worthwhile to investigate the impact of parental mortality on the prevalence of child labour in the country.

The remainder of the paper is organised as follows: Section 2 establishes the conceptual relationship between orphanhood and child labour. Section 3 presents the data and provides summary statistics for selected variables. The identification strategy is described in Section 4. Section 5 presents the results and discussions, including heterogeneity analysis, robustness checks, and mechanisms. Section 6 presents the conclusions and policy implications.

2. Conceptual Framework

The economic literature on child labour does not provide a single model that explains how child labour develops in a household or society. Alternative models of child labour exist, with certain common premises such as socially undesirable child labour and desirable child education and leisure, and parental decision-making authority over child labour. In the latter instance, parents are supposed to be benevolent and rational in optimising the welfare of the entire household, including that of the child (Jafarey and Lahiri, 2000). There are two probable pathways in the study for the effect of parental mortality on child labour: changes in household structure and decision-making processes, and changes in economic status. According to Edmonds (2007), the absence of a parent is likely associated with heterogeneity in family income and deferential investment incentives related to the biological relationship of the child's care-giver to the child.

Hamilton's rule suggests that an individual's level of altruism towards others is determined by their genetic proximity to them (Hamilton, 1963). Empirical evidence also indicates that individuals are more altruistic and treat those with whom they have tight family ties preferentially over those with whom they are distantly linked (Hamilton, 1963; Case et al., 2004; Anderson, 2005; Kazeem and Jensen, 2017). Orphanhood increases the likelihood of child labour decisions being made by non-parental caregivers, which can result in more child labour. Fors (2012), for example, emphasized the importance of parental altruism in child labour decisions. Numerous studies show lower school enrollment and attendance among orphans who are distantly connected to their household heads (Kazeem and Jensen, 2017; Case et al., 2004). In contrast, extended families and social networks are shown to shield orphans from the negative consequences of orphanhood (Beegle et al., 2010; Ardington and Leibbrandt, 2010; Foster et al., 1995; Motha, 2018; Abebe and Skovdal, 2010).

The impact of parental death on child labour may also arise as a result of the potential income shock that follows. The relationship between household economic position and child labour has been discussed for different settings. Child labour could be influenced by household wage earnings (Basu and Van, 1998), educational returns (Emerson and Knabb, 2006), or resource ownership, particularly land, combined with imperfectly functioning labour and land markets (Bhalotra and Heady, 2003; Basu et al., 2010; Shumetie and Mamo, 2019; Oryoie et al., 2017). In general, the empirical literature implies that child labour can be used as a coping mechanism against economic shocks (Duryea et al., 2007; De Janvry et al., 2006; Beegle et al., 2006b; Fabre and Pallage, 2015; Bandara et al., 2015; Baez et al., 2017; Dillon, 2013; Guarcello et al., 2010). Because of the numerous factors that contribute to child labour and the conflicting empirical findings, the relationship between parental death and child labour is unclear and could benefit from further analysis, as in this study.

3. Data and Summary Statistics

3.1. Data

This study makes use of Young Lives panel data from an International Study of Childhood Poverty in Ethiopia carried out by Oxford University. The dataset was obtained from the UK Data Service. During the first survey round in 2002, 2000 one-year-old children (referred to as the "younger" cohort) and 1000 eight-year-old children (referred to as the "older" cohort) were surveyed. The same youngsters were followed in five survey cycles until 2016. The sample was drawn from children living in 20 sentinel sites spread across the country's four major regional states, which account for 96% of the population. This study is based on the younger cohort because it encompasses children as young as 15 in the last round of the survey. This allows for the observation of critical outcomes that would have been censored if the older cohort had been used (individuals are beyond child labour age in three of the five rounds). The younger cohort's lower attrition rate, which is only 5.3% (9.3% including attrition due to death) from round 1 to 5, also gives an advantage against potential attrition biases (Young Lives, 2018).

3.2. Variables

The purpose of this study is to look into the dynamic impact of parental death on child labour. I measure child labour using alternative indicators. The daily proportion of child time spent on unpaid and paid activities at and/or outside the home is the primary indicator used. This is calculated by combining the proportion of time spent by a child on household care (caring for younger siblings and sick household members), domestic tasks (fetching water, firewood, cleaning, cooking, washing, and shopping), non-pay work (tasks on the family farm, cattle herding, shepherding, and other family business), and paid work (activities for pay outside of the household or for someone not in the household). The time spent on these activities is computed as the proportion of 24 hours allocated to different activities daily, including schooling, studying, sleeping, and leisure.

Alternative measures of child labour are constructed for robustness checks. The daily proportion of total child time is divided into unpaid household services (child time spent on household care and domestic tasks) and economic activities (non-pay or paid work). Unpaid household services are deemed non-economic activities since they are intended for self-consumption and are often outside the production boundaries of the System of National Accounts (Prifti et al., 2021; Dinku and Fielding, 2021). A child labour dummy based on UNICEF's standard indicator for child labour is also created for robustness checks. According to UNICEF's standard indicator, a child is considered a labourer if: i) they are between the ages of 5 and 11 and spend at least one hour per week on economic work or 21 hours per week on unpaid household services; ii) they are 12 to 14 years old and spend at least 14 hours per week on economic work or 21 hours per week on unpaid household services; and iii) they are 15 to 17 years old and spend at least 43 hours per week on economic work (UNICEF, 2021).

The key explanatory variable in this study is orphanhood (single or double). However, maternal and paternal orphans are treated separately to check for heterogeneity in the results. Other controls used in the study included place of residence, gender, BMI, age of the household head, household size, number of children aged 6 to 17, dependency ratio, sex ratio, household wealth index, access to sanitation, access to safe drinking water, access to services index, paternal illness, crop failure, religion, and region.

3.3. Sample Selection

In round 1 of the Young Lives data 2,000 1-year-old children were tracked in subsequent rounds until they were 15 in round 5. I use data from rounds 2 to 5 to match the UNICEF definition of child labour, which includes children aged 5 to 17 years. The round 2 data, hereafter referred to as the main baseline, contains 1,912 children. I eliminated children who had lost either of their parents in rounds 1 and 2, leaving only children whose parents were alive in round 2 (the main baseline). After excluding 134 children who lost either of their parents in the first two rounds and persons surveyed in fewer than two rounds of data, an average of 1,574 individuals in each round were included for analysis, totalling 6,296 observations in the four rounds.

The resulting sample, referred to as the quasi-experimental sample henceforth, is then categorised into groups and sub-groups. In the main analysis, the overall impact of parental death on child labour is compared between orphans and non-orphans. Orphans are then separated into three sub-groups based on when they became orphans. These are children who were orphaned between consecutive survey rounds following the main baseline. The nature of the data that follows the children of the same age helps to link orphanhood timings into the ages of 6-8, 9-12, and 13-15. The impact of parental death by orphanhood timing is then investigated to provide more disaggregated results.

Based on the quasi-experimental unbalanced data, as shown in Figure 1, the number of orphaned children between the ages of 6-8, 9-12, and 13-15 is 41, 39, and 33, respectively. There are 113 orphans in all, accounting for 7.2% of the total quasi-experimental sample observations per round. The sample size in the main baseline (round 2 of the survey) is smaller than in later waves. This is primarily due to missing data on the outcome variable, child labour, in that survey round. This problem is accounted for in empirical estimations by utilising the immediate pre-orphanhood period as the baseline. In that instance, the baseline is round 3 and 4, respectively, for children who are orphaned between the ages of 9-12 and 13-15. The parallel trend conditions are also evaluated using pre-orphanhood information conditional on observed covariates.

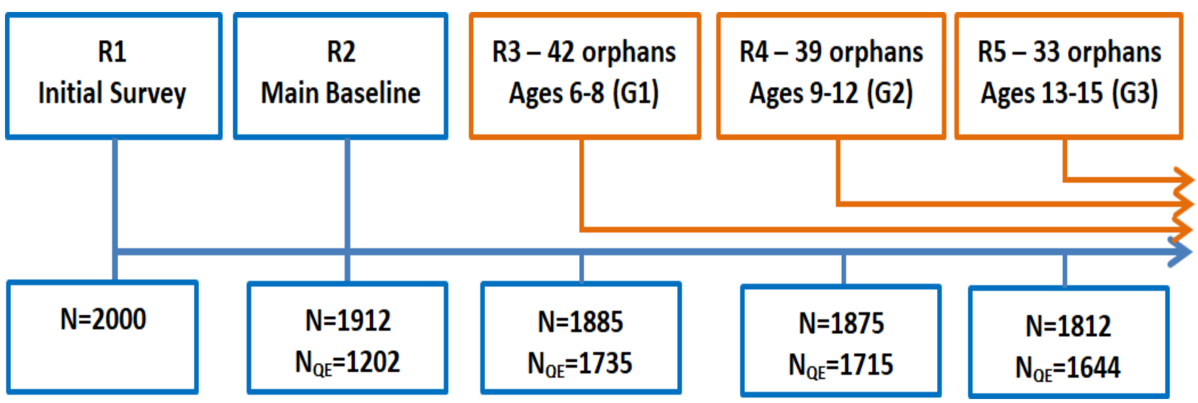

Figure 1: Structure of the full and quasi-experimental sample

3.4. Summary Statistics of Baseline Characteristics

The descriptive statistics of key variables based on the main baseline data from round 2 of the survey are provided in Table 1. The first two Columns (Columns 1 and 2) show the mean values of various attributes from the full and quasi-experimental samples, respectively. There are no discernible variations in the observed properties of the two samples. Before describing the empirical technique, it is also worthwhile to look for differences in observed features between orphans and non-orphans in the quasi-experimental sample. This provides insight into the various sources of time-varying unobserved heterogeneity that could contribute to biased estimates of the impact of parental death on child labour.

Table 1: Summary statistics and mean difference tests

	(1) Full sample	(2) Q.Exp. sample	(3) Non-orphans	(4) Future orphans	(5) Mean Diff.
Child labour (Prop. hrs)	7.11	7.36	7.409	6.765	0.645
Residence (Rural dummy)	0.65	0.67	0.670	0.647	0.023
Gender (Female dummy)	0.47	0.46	0.457	0.518	-0.061
BMI	14.53	14.56	14.567	14.503	0.064
Age of HH head	41.03	41.18	40.813	46.012	-5.199***
HH size	6.05	6.13	6.073	6.812	-0.738***
No. children 6-17 age	1.90	1.91	1.900	2.106	-0.206
Dependency ratio	31.90	32.11	32.226	30.560	1.665
Sex ratio (M/F)	1.18	1.21	1.204	1.263	-0.059
HH wealth index	0.30	0.30	0.298	0.327	-0.029
Access to sanitation	0.55	0.55	0.546	0.624	-0.077
Access to drinking water	0.59	0.56	0.557	0.647	-0.090*
Access to services	0.41	0.40	0.397	0.459	-0.061*
Crop failure	0.21	0.22	0.215	0.247	-0.032
Paternal illness	0.16	0.17	0.163	0.212	-0.049
Region					
Tigray	0.20	0.19	0.191	0.141	0.050
Amhara	0.20	0.21	0.209	0.176	0.032
Oromia	0.20	0.21	0.203	0.235	-0.032
SNNP	0.25	0.26	0.257	0.271	-0.014
Addis Ababa city adm.	0.15	0.14	0.141	0.176	-0.036
Religion					
Muslim	0.16	0.17	0.170	0.176	-0.006
Catholic	0.01	0.01	0.012	0.024	-0.012
Protestant	0.11	0.11	0.114	0.129	-0.016
Orthodox	0.71	0.69	0.690	0.671	0.020
N	1912	1202	1117	85	1202

Notes. This table presents descriptive statistics and mean difference tests of key variables using main baseline information (round 2 of the Young Lives data). Columns (1) and (2) show the mean values for the full sample and the quasi-experimental sample, respectively. The quasi-experimental sample contains observations with full information on key variables once children orphaned by round 2 are excluded from the sample. Columns (3) and (4) show the mean values for non-orphans and orphaned in subsequent waves, while Column (5) presents their mean difference tests. The mean difference tests are based on unequal variance (the result is also consistent when equal variance is assumed). ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

The mean difference tests of observable characteristics at the main baseline (round 2) between non-orphans (Column 3) and children who become orphans after round 2 (Column 4) are presented in Column 5 of Table 1. Most of the reported differences are statistically insignificant. However, there is a statistically significant difference in the age of the household head and family size between non-orphans and orphans. There are also marginally significant disparities in access to drinking water and services. Similar results are obtained using pre-baseline data (round 1). Such apparent discrepancies imply that they could contribute to biased estimates of the impact of parental death on child labour. To account for these and anticipated disparities between those orphaned in subsequent survey rounds and non-orphans, I control for variables on which the two groups differ as well as a vector of additional covariates.

The average share of time spent by children daily on unpaid and paid activities at and/or outside the house in the baseline or at the age of 5 years is approximately 7.36%. In the subsequence survey rounds, the proportion grew to 16.99% at the age of 8 (round 3), 17.31% at the age of 12 (round 4), and 19.17% at the age of 15 (round 5).

4. Identification Strategy

I use a conditional staggered Difference-in-Differences (DID) with multiple periods approach developed by Callaway and Sant'Anna (2020) to explore the dynamic impact of parental death on child labour. The DID setup used in this study utilizes the irreversible nature of orphanhood and disparities in the timing of orphanhood. Though all children are non-orphans in the main baseline (round 2), children who lose either of their parents in round 3 (ages 6-8), round 4 (ages 9-12), or round 5 (ages 13-15) will continue to be orphans. Taking this into consideration, I conduct a multi-level analysis to investigate the overall impact of orphanhood on child labour, the effect of differences in the timing of orphanhood, the effect at different ages of the children, and a more disaggregated analysis that combines the effect of the timing of orphanhood at different ages of the children.

Given that parental death is unlikely to be distributed randomly; cross-sectional differences between orphans and non-orphans may determine both orphanhood and child labour. To account for this, pre-orphanhood differences in individual and household characteristics, including variables in which future orphans and never-orphans initially differ are controlled (see Table 1). Conditional on these covariates, an improved doubly robust DID estimator based on inverse probability of tilting and weighted least squares (Callaway and Sant'Anna, 2020) is used to satisfy the pre-orphanhood parallel trend condition, which is assumed to extend to post-orphanhood in the absence of parental death. For both the estimation of the propensity score and outcome regressions, the earliest period pre-orphanhood covariates are used.

Though individual and household heterogeneity that can attribute to differences in child labour and orphanhood are partially accounted for by controlling for them, there may be omitted variables that correlate with the variables of interest. For this, I employ estimations that contain individual and survey-round fixed effects. The latter accounts for the potential impact of age differences on child labour, as children of the same age are followed in each round of the survey. The DID estimation also allows the study to account for the time-invariant individual fixed effects. For inference, standard errors are clustered at the community level. Taking all of this into consideration, the child labour outcomes of orphanhood are unobservable if parental death had not occurred. As a result, never-orphans can serve as a counterfactual to the outcomes of orphans. Alternatively, because of the availability of multiple periods and differences in the timing of orphanhood, not-yet-orphans can be used as a counterfactual. The latter is selected as the counterfactual in the main estimations due to the higher possibility of orphans eventually differing from the never-orphan group. Not-yet-orphans are children who are never-orphans and future orphans. The panel data and differences in orphanhood timing also allow the estimations to use the most recent non-orphan period as the "base period" and the current period as the "post period." Formally, I estimate the average overall impact of parental death on child labour as:

$$Child\ Labour_{i,t} = \beta Orph_{i,t} + \gamma X_{i,t} + \theta_i + \mu_t + \epsilon_{i,t} \dots\dots\dots\dots\dots\dots\dots\dots (1)$$

where $Child\ Labour_{i,t}$ represents child labour indicators of child *i* at time *t*. $Orph_{i,t}$ is a dummy variable that indicates whether child i has lost at least one of their biological parents between the survey rounds by the time t. For heterogeneity, separate estimations are run for the father's and mother's deaths. $X_{i,t}$ is a vector of child and household characteristics used to maintain a pre-orphanhood parallel trend. These include place of residence, gender, BMI, age of the household head, family size, number of children aged 6 to 17, dependency ratio, sex ratio, household wealth index, access to sanitation, access to safe drinking water, access to services index, paternal illness, crop failure, religion, and region. It is important to note that the earliest-period pre-orphanhood covariates are used as a baseline. θ_i is individual fixed effects, and μ_t is year fixed effect. β, and γ are parameters.

The DID with a multiple period estimator allows me to break down the average total impact into the following components: the effect by orphanhood timing differences (orphaned between the ages of 6-8, 9-12, and 13-15), the effect at different ages of the children (at ages 8, 12, and 15), the effect at different ages of the children for each group orphaned over different periods (e.g. the effect for those who are orphaned between the ages of 6-8 and the impact at their age of 8, 12, and 15), and the effect by length of exposure to orphanhood. To account for all of this and reveal the dynamic effect of parental death on child labour, equation 1 in the prior model is re-specified as follows:

$$Child\ Labour_{i,t} = \sum_{m=1}^{N} \beta_m Orph_{i,t+m} + \sum_{n=0}^{N} \beta_n Orph_{i,t-n} + \gamma X_{i,t} + \theta_i + \mu_t + \epsilon_{it} \dots\dots (2)$$

where $Orph_{i,t+m}$ denotes if individual *i* will experience parental death in *m* periods in the future, and $Orph_{i,t-n}$ denotes whether individual *i* has experienced parental death in *n* prior periods. The purpose of this analysis is to evaluate the significance of β_m, which captures pre-existing trends in child labour, whereas β_n accounts for a lag in the effects of parental death and treatment heterogeneity by exposure time.

5. Results and Discussions

5.1. Main Findings

The main estimation, presented in Table 2, evaluates the average overall impact of parental death on child labour, which is measured as a daily share of a child's time on unpaid and paid activities within or outside the home. Estimations in Columns (1) to (3) use never-orphaned children as counterfactual, while the estimation in Column (4) uses not-yet-orphaned children. All the estimations also account for individual and time-fixed effects. Column (1) presents results from unconditional staggered DID, where cross-sectional differences that might determine both orphanhood and child labour are not controlled. The finding indicates that parental death has a positive contribution to child labour. The unconditional staggered DID has been criticised because it does not account for differences in observed characteristics that could result in non-parallel outcome dynamics between orphans and non-orphans. As a result, the estimator may fall short of recovering relevant causal parameters of interest (Callaway and Sant'Anna, 2020).

Table 2: Overall average effect of orphanhood on child labour

	(1)	(2)	(3)	(4)
Parental Death (ATT)	1.591**	2.010***	2.173***	2.271***
	(0.810)	(0.716)	(0.585)	(0.580)
Other controls	No	Yes	Yes	Yes
Counterfactual	Never-orphans	Never-orphans	Never-orphans	Not-yet-orphans
Par. trend ass. (P-value)		0.305	0.481	0.481
Observations	6263	6263	6263	6263
Mean dep. var.	15.81	15.81	15.81	15.81

Notes. This table presents the results of a staggered DID with multiple period regression on the impact of parental death on child labour using four rounds of the Young Lives data. Column (1) reports the results of unconditional staggered DID. Column (2) presents the results of conditional staggered DID controlling for age of the household head, household size, access to drinking water, and access to services. Column (3) reports the results of conditional staggered DID accounting for additional covariates. The earliest-period pre-orphanhood covariates are used as baseline data. Estimations in Columns (1) to (3) used never-orphaned as counterfactual. Column (4) repeats the estimation in Column (3), but with not-yet- orphaned as counterfactual. Not-yet-orphaned include never-orphaned and future-orphaned children. Standard errors reported in parentheses are clustered at the community level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

In response to the estimation flaw in Column (1), I first accounted for the age of the household head, family size, access to drinking water, and access to services, on which prospective orphans and never-orphans were found to vary in the main baseline. Based on this, as indicated in Column (2), we fail to reject the parallel trend assumption, which holds that the control variables are sufficient to yield comparable orphan and non-orphan groups. Taking this into account, the results suggest that parental death has a statistically significant positive impact on child labour. Column (3) introduces additional controls such as place of residence, gender, BMI and its square, number of children aged 6 to 17 living in the household, dependency ratio, sex ratio, household wealth index, access to sanitation, paternal illness, crop failure, region, and religion. The result is consistent with the findings in Column (2), but with a larger effect.

The results of conditional staggered DID based on control variables are shown in Column (4) of Table 2, with the "not-yet-orphaned" group serving as a counterfactual. The presence of different timings of orphanhood with multiple time periods allows use of the not-yet-orphaned as a counterfactual without modifying the sample. Parental death, like prior estimates, has a statistically significant impact on child labour. Orphans spend more time on unpaid and paid activities within or outside of the home than non-orphans. Orphans have a 2.3 percentage point greater daily child labour share of unpaid/paid activities than non-orphans. This accounts for about 14.6% of the average daily time spent by children on unpaid/paid activities within or outside the home. This translates to more than a half-hour (33 minutes) difference in time spent daily on child labour by orphans versus non-orphans. The findings are consistent with those of previous research, which has shown that parental illness or death is linked to increasing child labour. Kamei (2018), for example, identified hazardous child labour caused by the loss of a father. Other studies have also shown a link between negative parental health outcomes (disability or illness) and higher rates of child labour (Edmonds, 2010; Woode, 2017; Dinku et al., 2018).

In this study, the extent of the impact of parental death on child labour is comparable to the impact of other factors on child labour in Ethiopia. Using the Ethiopian Rural Household Survey (ERHS), Colmer (2021) discovered that a one standard deviation increase in rainfall variability is related to a 2.2 and 0.4 percentage point decrease in the likelihood of engaging in farm work and paid work, respectively. Dinku (2019) investigated the impact of a safety net scheme and discovered that children in beneficiary households are around 13 percentage points less likely to be in child labour than children in non-beneficiary households. Similarly, Prifti et al. (2021) found that an unconditional transfer programme in northern Ethiopia reduced the total number of hours worked by children from beneficiary households by half an hour per day.

The estimation approach, as demonstrated in equation (2), helps to break down the overall average effect presented in Column (4) of Table 2 into the effect by orphanhood timing, at different ages of the child, and by length of orphanhood exposure. Panel (a) of Table 3 decomposes the effect by orphanhood timing. That is, it provides a distinct average treatment effect for the three orphan age groups, that is, those who have lost their biological parents between the ages of 6-8, 9-12, and 13-15. According to the findings, parental death has a statistically significant effect on child labour for those who are orphaned early in their lives. Those who lost their parents between the ages of 6-8 have a 2.9 percentage point higher daily share of paid and unpaid activities than non-orphan children of the same age. The effect here is the sum of orphanhood's immediate and long-term effects on child labour for that age group. A consistent result is obtained for the group of children who have lost their biological parents between the ages of 9-12, with a 2.6 percentage point difference in the daily child labour share between orphans and non-orphans. The smaller size of the effect in the latter case could be attributed to the shorter duration of orphanhood exposure. The effect of parental death on child labour is statistically insignificant for the group that experienced parental death between the ages of 13-15 years, where the effect is also negative. The disparities in economic and statistical size effects are indicative of differences possibly attributable to orphanhood timing.

Table 3: Disaggregated average effects by orphanhood timing, age, and length of exposure

Orphanhood Timing (a)	Age 6-8	Age 9-12	Age 13-15	Average	
	2.905**	2.588**	-0.410	1.763***	
	(1.372)	(1.230)	(1.638)	(0.581)	
Age Effect (b)	**Effect at 8**	**Effect at 12**	**Effect at 15**	**Average**	
	1.504	3.242***	1.831**	2.192***	
	(1.834)	(0.991)	(0.919)	(0.737)	
Length of Exposure (c)	**LE - 0**	**LE - 1**	**LE - 2**	**Post_avg**	**Pre_avg**
	1.835*	1.801*	4.957	2.864***	-1.605
	(0.984)	(1.032)	(3.408)	(1.032)	(1.313)

Notes. This table reports disaggregated results from conditional staggered DID with multiple period regression, which controls for covariates and uses not-yet-orphaned as counterfactuals. Panel (a) reports disaggregated results by orphanhood timing, which summarises the average effects by the age at which the children experienced parental death. Panel (b) presents age-disaggregated results, which summarize the effect of orphanhood at different ages of the victims. Panel (c) reports the average effects based on the length of orphanhood exposure. All of the other conditions listed in Column (4) of Table 2 are satisfied. Standard errors reported in parentheses are clustered at the community level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel (b) of the table examines the impact of parental death on child labour at various ages. The effect of parental loss at the age of 8 assesses the impact of parental death on child labour at the age of 8 for those who lost their parents between the ages of 6-8. The effect at age 12 represents child labour outcomes at the age of 12 for children who are orphaned between the ages of 6-8 and 9-12. The same compositional line applies to the effect at 15 years old. There is a statistically insignificant effect at age 8, which could be due to a lower likelihood of engaging in work at this age. At the ages of 12 and 15, however, the impact of parental death on child labour is statistically significant. When compared to non-orphans, the effect of parental mortality resulted in a 3.2 percentage point increase in the daily share of child labour at the age of 12. At the age of 15, the statistical and economic size of the impact of parental death on child labour decreases. That is, by the age of 15, the margin had fallen to only 1.8 percentage point. If the duration of exposure mattered in this scenario, we would expect parental death to have a more economically and statistically significant impact on child labour at the age of 15, as these are groups of children who had lost their parents between the ages of 6-8, 9-12, and 13-15. However, the impact appears to be slightly reversed due to the negative and statistically insignificant effect of parental death on the child when it occurs when the child is between the ages of 13-15.

The average treatment effects by length of exposure are shown in Panel (c) of Table 3. The effect of parental death on child labour is only marginally significant (at 10% level of significance) for exposure lengths of zero (immediate effect) and two. When this result is combined with the findings in panels (a) and (b), the significance at the exposure length of zero may be attributable to the significant immediate impact for those who are orphaned between the ages of 9-12, as opposed to earlier or later ages. Similarly, the statistically significant effect at exposure length of one could be owing to the statistically significant impact of parental death at the age of twelve for those who lost their parents between the ages of 6-8, albeit the effect at the age of eight is statistically insignificant. The pre- and post-orphanhood average effect also supports the parallel trend assumption, as the difference in child labour between orphans and non-orphans before orphanhood is statistically insignificant.

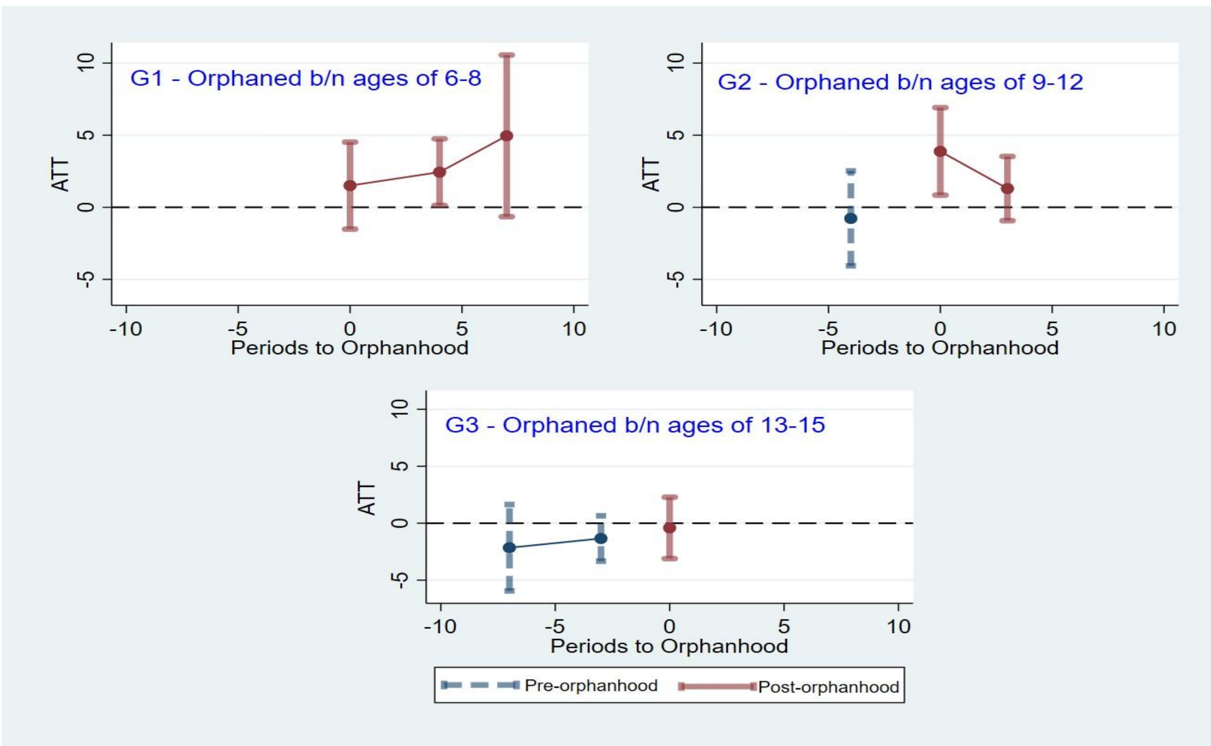

Figure 2: Dynamics of orphanhood timing specific average effects

The graphs depict the dynamic effect of parental death on child labour, which is disaggregated by orphanhood timing and age at orphanhood. The bars reflect a 90% confidence interval.

I next divided the effect by orphan groups, classified based on the timing of orphanhood, to investigate the impact at different ages of the children, as shown in Figure 2. The figure at upper left depicts the effect of parental death on child labour for children who lost their parents between the ages of 6-8. Despite the fact that parental death has a positive and increasing impact on child labour, it is only marginally significant when children are 12 years old. The short-run impact on those who have lost a parent between the ages of 9-12 is positive and statistically significant. The short-term effect for children who lost their parents between the ages of 13-15 is, on the other hand, statistically insignificant. Based on these findings, it is reasonable to conclude that parental death has no effect on child labour at the age of 15 years, regardless of the time of orphanhood. This is also confirmed by using round 2 (12 years old) and round 3 (15 years old) of the older cohort Young Lives data (see Appendix Table A.1 for the detail).

The pre-orphanhood results demonstrate a statistically insignificant difference between future orphans and non-orphans, as illustrated in the upper right and bottom panels of Figure 2, corroborating the pre-orphanhood parallel trend conditioned on individual-level factors. Similarly, using the main baseline data, it has been demonstrated that future orphans and non-orphans are identical in most of the observed characteristics, including the outcome variable. With the pre-orphanhood parallel trend conditions intact, we anticipate the post-orphanhood parallel trend to continue without the subject of treatment, orphanhood.

In general, child labour owing to parental death is statistically significant at the age of 12, as opposed to earlier or later ages. This finding is congruent with the findings of Seid and Gurmu (2015), who observed that the average marginal effect of age cohorts on the probability of child labour peaks around the age of 12 years old, with an inverted U-shape type of age and child labour association. Similarly, Haile and Haile (2012) discovered that the marginal effect on the probability of child labour paired with schooling is stronger at the age of 9-12 years old than at earlier or later child ages. This could be because they are at very early child age at the age of 8 and old enough at the age of 15 to make their own time allocation decisions, lowering the chance of child labour exploitation.

5.2. Heterogeneity Analysis

A previous section of this paper investigated the impact of parental death (single or double orphanhood) on child labour. The impact of maternal and paternal orphanhood on child labour is examined separately in this section. Maternal orphanhood is statistically significantly likely to increase child labour, as shown in Column (2) of Table 4, whereas paternal death is statistically insignificant in relation to child labour, as shown in Column (1). The death of a mother increases a child's time spent on paid and/or unpaid activities within or outside the home by 4.7 percentage points, accounting for approximately 30% of daily child time spent on these activities. This finding is consistent with earlier findings that mother-child health shocks have a stronger effect on child outcomes. According to Dinku et al. (2018), maternal illness raises the likelihood of child labour by 9.6% in Ethiopia, while paternal illness has no influence on child labour. Similarly, there is evidence that maternal mortality has a greater negative effect on children's educational outcomes (Evans and Miguel, 2007; Case and Ardington, 2006).

Columns (3) to (6) of Table 3 exhibit heterogeneity analysis by child gender and place of residence. For both sexes, parental death has a positive and statistically significant effect on child labour. Male and female children spend equal amounts of time each day on paid and unpaid activities, with parental death having a comparable impact on child labour. However, there is no statistically significant effect of parental death on child labour for children living in urban areas, while there is a positive and statistically significant effect for children living in rural areas. This could be attributed to more child work activities in rural settings than urban ones. This is also evidenced by the greater disparity in the average share of daily child time spent on paid and unpaid activities between urban and rural children. The proportion of a child's daily time spent on activities for rural children (19.4%) is more than double that of urban children (8.8%).

Table 4: Heterogeneity analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Overall Effect - ATT			Male	Female	Urban	Rural
Paternal Death	1.330					
	(0.930)					
Maternal Death		4.569***				
		(1.606)				
Parental Death			2.275*	2.405*	0.875	3.065***
			(1.312)	(1.366)	(0.718)	(1.189)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6281	6260	3332	2912	2046	4112
Mean dep. var.	15.81	15.81	15.93	15.67	8.83	19.39

Notes. This table reports the results of a staggered DID with multiple period regression on the impact of orphanhood on child labour. Columns (1) and (2) present the impact of paternal and maternal orphanhood on child labour, respectively. Columns (3) to (6) detail the gender and location-based impact of parental death on child labour. The estimations account for other covariates and use not-yet-orphaned as a counterfactual. Standard errors reported in parentheses are clustered at the community level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

5.3. Robustness Checks

In this section, the robustness of the preceding results is examined using alternative child labour measures. Column (1) of Table 5 contains a child labour dummy constructed using UNICEF's standard child labour indicators, as detailed in the Data and Summary Statistics Section. Parental death has a statistically significant effect on child labour, consistent with the main model results. That is, orphaned children are 11% more likely than non-orphaned children to engage in child labour. This effect is stronger than that shown of other variables related to child labour. These include findings of a 2.2% decrease in the likelihood of children engaging in farm work as a result of a one standard deviation increase in rainfall variability (Colmer, 2021), a 9.6% increase in the probability of child labour following maternal illness (Dinku et al., 2018), a 3.8% decrease in the probability of a child working as a result of one additional health extension worker in a community (Posso et al., 2021), and a 5 percentage point reduction in the share of child labour as a result of a government transfer programme (Prifti et al., 2021). However, the effect is lower than the 13 percentage point less likelihood of child labour following introduction of a public works programme (Dinku, 2019), and a 13% increase in child labour in households that adopt soil and water conservation practices (Fontes, 2020).

Table 5: Robustness checks

	(1) CL Dummy	(2) CL Non-EconAct	(3) CL EconAct
Overall Effect - ATT (a)			
Parental Death	0.114***	1.565**	0.707
	(0.044)	(0.629)	(0.734)
Orphanhood Timing - (b)			
Age 6-8	0.188***	1.301	1.604
Age 9-12	0.090	1.799*	0.789
Age 13-15	-0.042	1.755	-2.165*
Age Effect - (c)			
Effect at age of 8	0.077	1.126	0.378
Effect at age of 12	0.127**	1.769**	1.472
Effect at age of 15	0.117**	1.561**	0.270
Other controls	Yes	Yes	Yes
Par. trend assum. (P-value)	0.792	0.519	0.998
Observations	6263	6263	6263
Mean dep. var.	0.54	9.64	6.17

Notes. This table presents the findings of a staggered DID with multiple period regression on the impact of parental death on alternative child labour metrics. The child labour dummy is constructed using UNICEF's definition of child labour. Child labour on non-economic activities, and child labour on economic activities are alternate metrics of child labour used and presented in Columns (1) to (3), respectively. Panel (a) displays the overall average effect. The disaggregated effect by orphanhood timing and age is presented in panels (b) and (c), respectively. All the estimations accountfor other covariates and use not-yet-orphaned as a counterfactual. Standard errors reported in parentheses are clustered at the community level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Columns (2) and (3) of Table 5 present the impact of parental death on child labour on non-economic (unpaid household services such as care and domestic chores) and economic (unpaid and paid work at a farm, family business, or for non-family members) activities, respectively. The findings demonstrate that parental death has a statistically significant positive effect on daily child labour share in non-economic activities, such as caring for household members, fetching water, collecting firewood, cleaning, cooking, washing, and shopping. Children who have lost either of their biological parents spend 1.6 percentage points more time per day on the aforementioned non-economic activities, accounting for around 16.6% of the average amount of daily time spent by all children on these activities. However, parental death has no statistically significant effect on child time spent on economic activities such as non-pay work on the family farm, cattle herding, shepherding, and work in other family businesses, or paid work outside the household. This means that child labour in Ethiopia carries a heavier burden of unpaid household services. The summary statistics in the table show that the daily share of child labour on unpaid household services is 9.63%, accounting for more than 60% of total average child labour time. Domestic activities, are culturally and socially allotted to women in developing countries like Ethiopia, and this conclusion, together with the findings of heterogeneity analysis, suggests that maternal death shifts the load of these domestic activities, onto the shoulders of children.

According to Cockburn and Dostie (2007), roughly 59% of Ethiopian children aged 6 to 15 are engaged in paid or unpaid work, with the majority undertaking domestic tasks such as collecting wood and fetching water. Consistent with the preceding finding, Prifti et al. (2021) discovered that following unconditional government transfers, the reduction in child labour in the urban context is primarily attributed to a reduction in children's involvement in household chores, whereas in the rural context, household chores and farm work are equally affected. In contrast Colmer (2021) discovered that rainfall variability had a statistically significant effect on the chance of children engaging in agricultural and paid employment but not on domestic work. Given the obvious association between rainfall variability and farm activity in an agriculture-dependent country like Ethiopia, this is understandable.

The results are also consistent when disaggregated by orphanhood timing and age, as shown in panels (b) and (c) of Table 5. The results in Columns (1) and (2) reveal that parental death has a stronger impact on child labour for those who lose their parents at a young age. The impact is also evident in the child's later years. That is, the age-specific effect demonstrates a statistically significant impact of parental death on child labour at the ages of 12 and 15, with a larger effect at the age of 12.

This study is based on an unbalanced quasi-experimental panel data sample chosen based on a predefined criterion. This type of non-random sampling could lead to biased estimates. Alternative attrition bias tests are run to ensure that the results are consistent (see Appendix Table A.2 for details). First, the estimation of the key results provided in Table 2 of Column (4) is replicated using a sub-sample of children observed in all four rounds with balanced panel data. The result is similar to the main findings. Second, the attrition bias test utilising the Wooldridge approach is also considered (Wooldridge, 2010). The number of successive waves from each period t is included as an additional variable in the main estimation shown in Table 2 Column (4). The impact of parental death on child labour is still statistically significant, albeit of slightly greater magnitude. The test results, therefore, suggest that the findings in the main estimations are unlikely to be biased due to attrition.

5.4. Plausible Mechanisms

According to Edmonds (2010), the effect of parental death on children's time allocation for education and labour could result from income shock or a change in the structure of household decision-making caused by parental death. In relation to the latter, according to Jafarey and Lahiri (2000), employing children is a parental decision related to promoting the welfare of the household. This is consistent with Hamilton's rule, according to which individuals are more altruistic towards those with whom they have close kinship ties (Hamilton, 1963; Case et al., 2004; Anderson, 2005; Kazeem and Jensen, 2017). The death of a parent who is a household head or child carer with more bargaining power to limit child labour could therefore lead to an increase in child labour. According to Kamei (2018), the incidence of child labour rises as decision-makers become less concerned about the detrimental consequences of child labour on child development. Edmonds and Shrestha (2013) also offered evidence that children who are not supervised by their parents are more likely to engage in child labour.

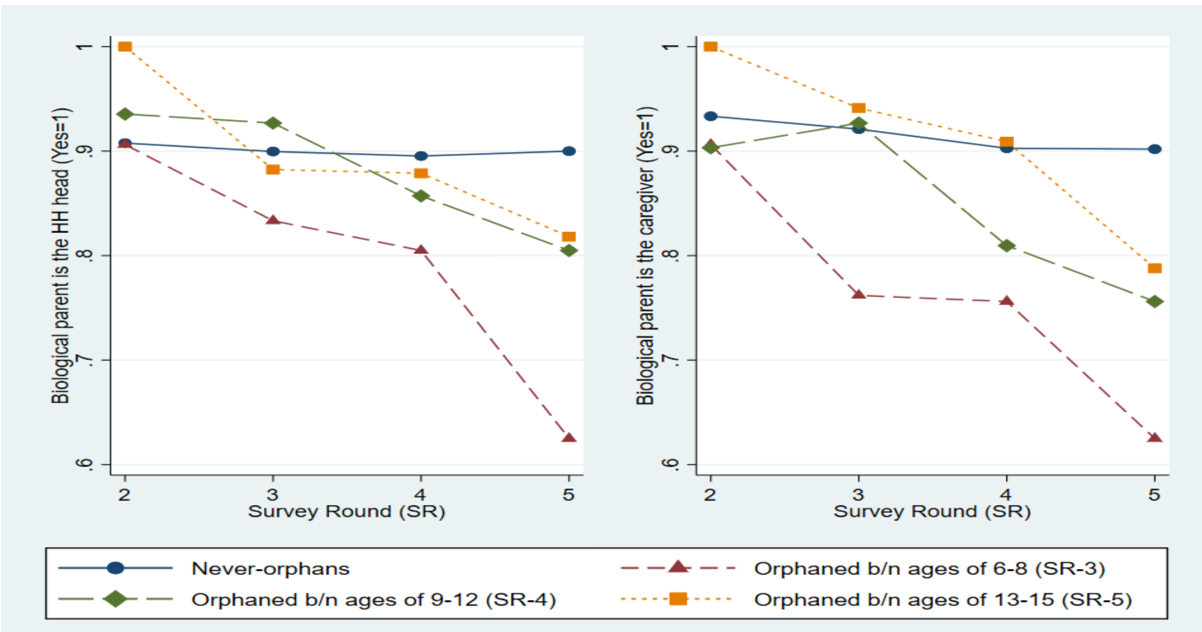

Figure 3: Household head and caregiver relationship to the sample children

The graph shows whether the biological parent is the household head and carer, disaggregated by orphanhood timing across waves. The proportion of children whose household head is their biological parent is plotted on the left, and the proportion of children whose caretaker is their biological parent is plotted on the right.

The trend of the household head and caregiver's relationship to the sample children is depicted in Figure 3. Following the aforementioned discussion, we anticipate a shift in the relationship of the household head and caretaker with the child, which could be one cause for a statistically significant association between parental death and child labour. In line with this, while there is a high tendency for the loss of biological parents to result in a change in the household head and carer for the child, this will be obvious only if the child loses both of their biological parents. According to the data used for this study, nearly 7% of the sample children have lost one or both of their biological parents, but only 0.38% have lost both, accounting for only 5.5% of those who have lost one parent or both parents.

According to the trend, over 90% of never-orphaned children have biological parents who are their household head or caregiver. However, the outcome for those who have lost either or both parents differs depending on when they became orphans. Initially, more than 90% of future orphans had a biological parent who served as the household head and carer. Those who lost a biological parent by the age of 6-8, on the other hand, have a continuously diminishing fraction of their biological parents staying as their household head or carer. Those who lost their biological parents between the ages of 9-12 and 13-15 still show a diminishing post-ante trend, as expected. When children who have lost both of their biological parents are excluded from the data, the trend follows a similar pattern (see Figure A.1 in the Annex). This is a clear indicator of a shift in the household structure following parental death, with possible child labour repercussions.

The second potential pathway for parental death leading to child labour is parental death-related wealth or income shock. The broader literature demonstrates the use of child labour as a coping strategy against economic shocks (Duryea et al., 2007; De Janvry et al., 2006; Beegle et al., 2006b; Fabre and Pallage, 2015; Bandara et al., 2015; Baez et al., 2017; Dillon, 2013; Guarcello et al., 2010). More specifically, parental death may be followed by an income shock, resulting in child labour as a mitigating mechanism. According to Kamei (2018), in Nepal, the death of a father resulted in children engaging in hazardous forms of child labour. Edmonds (2010) also demonstrated that paternal disability leads children into the most heinous forms of child labour. According to Edmond, the main mechanism that induces children to engage in hazardous forms of child labour is a decrease in household resource holding and earning options. However, a decline in resource ownership following paternal death may be linked to a decrease in child labour. According to Basu et al. (2010), households with large land holdings are more likely to send their children to work on their own farm. In support of this, Shumetie and Mamo (2019) discovered a positive relationship between household resources (livestock and cropland) and child labour in Ethiopia.

In this study, I first used a wealth index constructed from three indices – housing quality, access to services, and ownership of consumer durables – to shed light on the binding role of parental death-related wealth shock on child labour. Simple trend analysis is used to examine the path of the wealth index for never-orphans and three groups of orphans classified based on orphanhood timing. The results show no clear correlation between parental death and household wealth (see Annex Figure A.2). The theoretical and empirical literature reports that changes in household resources are frequently connected with paternal death, particularly in developing countries where the father is regarded as the breadwinner. As a result, a separate wealth trend analysis is performed using paternal death alone, and consistent results are obtained (see Annex Figure A.3). Recognising disparities in wealth and income, the study also utilises a dummy economic shock variable that incorporates job, source of income, and family enterprise losses for a household, to ensure consistency of results. There is no apparent link between income shock and parental death that could be associated with child labour, regardless of whether either a parent or a father dies (see Annex Figure A.4).

Of interest is the link between child labour and educational outcomes in the presence of parental death. The main concern with child labour is its short- and long-term effects on children's health, education, and livelihoods. According to the International Labour Organization, child labour is work that deprives children of their childhood, potential, and dignity, as well as work that is harmful to their physical or mental development. Child labour is associated with less likelihood of attending school, and a greater chance of dropping out early, or attempting to combine school attendance with excessively long and heavy work. To shed some light on this, the effect of parental death on school enrolment, schooling time, and study hours is estimated in this study. Column (1) of Table 6 reveals that parental death has a statistically significant and negative effect on child school enrolment. School enrolment is 8% lower on average for orphans than for non-orphans. The effect is statistically significant for children who lost one or both of their biological parents early in their lives (between age 6-8). Furthermore, the impact is statistically and economically larger for children of earlier schooling age.

Columns (2) and (3) demonstrate the disparities in daily schooling and study hours between orphans and non-orphans. Although there is no statistically significant difference in the daily share of time spent in school, there is a negative and statistically significant difference in the share of hours spent studying. That is, orphans spend less time studying than non-orphans. The finding is consistent with earlier studies that show the negative impact of parental death on educational outcomes and human capital accumulation (Beegle et al., 2006a; Case and Ardington, 2006; Case et al., 2004; Cas et al., 2014; Evans and Miguel, 2007; Gertler et al., 2004; Senne, 2014; Amato and Anthony, 2014; Gimenez et al., 2013). The lack of an effect of parental death on schooling time is also consistent with other studies, as children in Ethiopia often combine school attendance and work (Prifti et al., 2021; Seid and Gurmu, 2015; Haile and Haile, 2012).

In general, the findings here support our expectation that child labour has a potential crowding-out effect on children's educational time, though the effect of parental death on school attendance is minor. Children who have lost their biological parents are more likely to engage in child labour, with a lower school enrolment rate and less study time. This claim is consistent with prior research that found opposing effects of various factors on child labour versus educational outcomes (Colmer, 2021; Dinku et al., 2018). Child labour has also been linked to poorer educational outcomes (Dinku et al., 2019; Mussa et al., 2019; Dinku and Fielding, 2021).

Table 6: The impact of parental death on educational outcomes

	(1) Enrolment	(2) Schooling	(3) Studying
Overall Effect - ATT (a)			
Parental Death	-0.088***	-1.181	-0.788**
	(0.029)	(0.721)	(0.375)
Orphanhood Timing (b)			
Age 6-8	-0.130**	-1.526	-1.245**
Age 9-12	-0.098	-2.161*	-0.061
Age 13-15	0.059*	2.321***	-1.271
Age Effect - (c)			
Effect at age of 8	-0.172***	-2.918	-0.826
Effect at age of 12	-0.107**	-1.336	-0.649
Effect at age of 15	-0.049	-0.511	-0.874
Other controls	Yes	Yes	Yes
Par. trend assum. (P-value)	0.356	0.990	0.522
Observations	6233	6263	6263
Mean dep. var.	0.68	19.28	5.01

Notes. This table presents the findings of a staggered DID with multiple period regression on the impact of parental death on child educational outcomes. Column (1) shows results of employment of a school enrolment dummy as an outcome, whereas Columns (2) and (3) show the daily share of child time spent on schooling and studying, respectively. The overall average effect is depicted in panel (a). Panels (b) and (c) show the effect disaggregated by orphanhood timing and age, respectively. All the estimations accounted for other covariates and used not-yet-orphaned as a counterfactual. Standard errors reported in parentheses are clustered at the community level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

6. Conclusion

In the late 1990s and early 2000s, the HIV/AIDS pandemic was the major cause of orphanhood, with the highest prevalence in Sub-Saharan Africa (Beegle et al., 2006a; Case and Ardington, 2006; Evans and Miguel, 2007). Similarly, the COVID-19 epidemic resulted in an estimated 10.5 million children losing their parents and carers worldwide in 2019 alone (Hillis et al., 2022). Researchers and policymakers were drawn to such events to explore their effects on child development. Child labour, which jeopardises the short- and long-term well-being of children, is also on the agenda of national and international organisations. Despite the United Nations Sustainable Development Goal (SDG) of eliminating all kinds of child labour by 2025, the prevalence of child labour remains extremely high in developing countries. According to UNICEF’s estimate, 160 million children were in child labour worldwide at the start of 2020, with more than half of them in Sub-Saharan Africa (ILO and UNICEF, 2021).

This study investigates the dynamic impact of parental death on child labour, which has received insufficient attention in prior studies. The analysis is based on data from the Young Lives Survey

2002 - 2016, an International Study of Childhood Poverty in Ethiopia. Given the study's objective, children aged 5 to 15 are studied comprising a total of 6,388 observations. A conditional staggered DID with a multiple period estimator is used, with overall daily child time allocations (measured as a proportion of daily hours) on unpaid and paid activities at or outside the home serving as the main dependent variable and the death of one or both biological parents serving as the independent variable. The study also considers alternative measures of child labour and disaggregates parental death into maternal and paternal deaths for robustness and heterogeneity analysis. Cross-sectional heterogeneities are accounted for through the inclusion of individual observable characteristics, while time-invariant individual heterogeneities are accounted for through differencing.

The key regression results suggest that parental death has a statistically significant impact on child labour. Children who have lost either of their biological parents have a 2.3 percentage point higher daily child labour share than their counterparts. This accounts for approximately 13% of a child's daily time spent on unpaid or paid activities at home or outside of the home. Alternative estimations also show the following results: First, the cumulative effect of parental death is greater than the immediate effect, where children who are orphaned in their early years (between the ages of 6 and 8 years) are more affected than children orphaned at later ages. Second, the impact of parental death is greater at around age 12 than at earlier or later ages. Third, parental death forces children to perform unpaid household services (care and domestic work) rather than engage in economic activities (farm activities, work in family businesses, and paid work). Finally, maternal orphanhood has a greater impact on child labour than paternal orphanhood.

The results are consistent when a child labour dummy, built on UNICEF's standard indicator, is used as an outcome variable. In this case, children who have lost either of their biological parents are 11% more likely to engage in child labour. When the crowding-out effect of child labour on child education is examined, it is discovered that parental death has a statistically significant and negative effect on child school enrolment and study hours but has no effect on schooling time. As a result of the heterogeneous results, context-specific policy interventions and support programmes are required.

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Appendix A - Additional Tables

Table A.1: Overall average effect of orphanhood on child labour

	(1) Uncondid	(2) Condid	(3) CondidDum
Parental Death - ATT	0.672	1.129	-0.003
	(2.599)	(2.548)	(0.092)
Other controls	No	Yes	Yes
Observations	1570	1570	1570
Mean dep. var.	19.85	19.85	19.85

Notes. This table reports staggered DID with multiple period regression results on the impact of parental death on child labour using two rounds of the older cohort of Young Lives data. Column (1) reports unconditional staggered DID results based on the daily share of child time on paid and unpaid activities. Column (2) presents conditional staggered DID results using the same measure of child labour but controlling for other covariates. Column (3) reports the same estimation as in Column (2) but using a child labour dummy, constructed based on UNICEF's definition, as an outcome. All the estimations used not-yet-orphaned as a counterfactual. Standard errors reported in parentheses are clustered at the community level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table A.2: Robustness to attrition biases

	(1) Balanced Panel Data	(2) Woodridge attrition
Parental Death - ATT	2.398***	2.791***
	(0.700)	(0.719)
Other controls	Yes	Yes
Observations	4416	6231
Mean dep. var.	15.35	15.81

Notes. This table presents the results of a staggered DID with multiple period regression on the impact of parental death on child labour to test for attrition biases. Column (1) considers a balanced panel data sub-sample consisting only of children observed in all four rounds. Column (2) shows results of the same estimation as in Table 2 of Column (4) with the addition of an attrition variable. All the estimations used not-yet-orphaned as a counterfactual. Standard errors reported in parentheses are clustered at the community level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

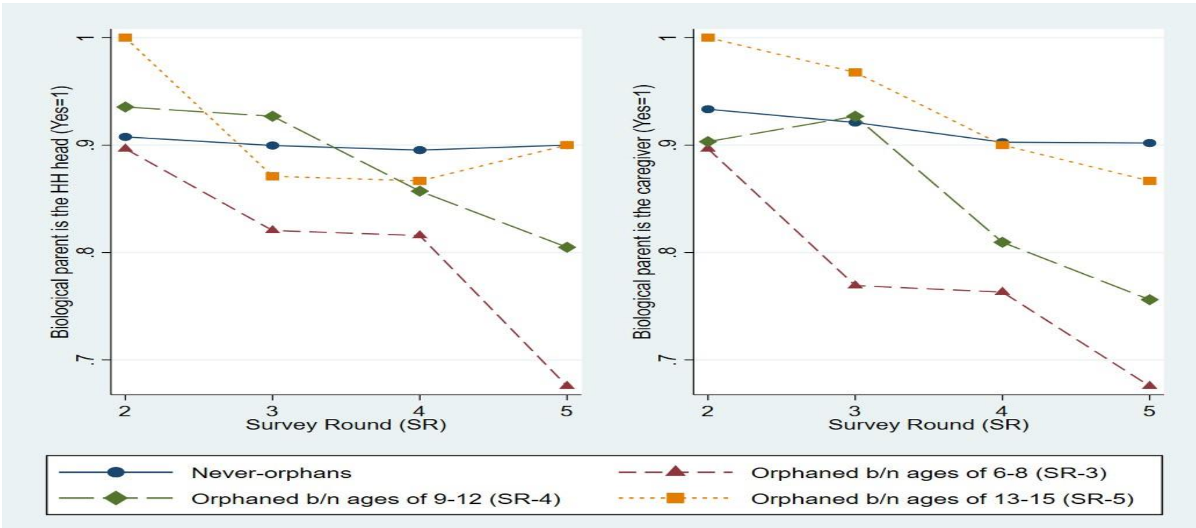

Figure A.1: Household head and caregiver relationship to the sample children

The graph shows whether or not the biological parent is the household head or carer, disaggregated by orphanhood timing across waves. Double orphans are eliminated from the data, and only single-parent orphan data are used. The proportion of children whose household head is their biological parent is plotted on the left, and the proportion of children whose caretaker is their biological parent is plotted on the right.

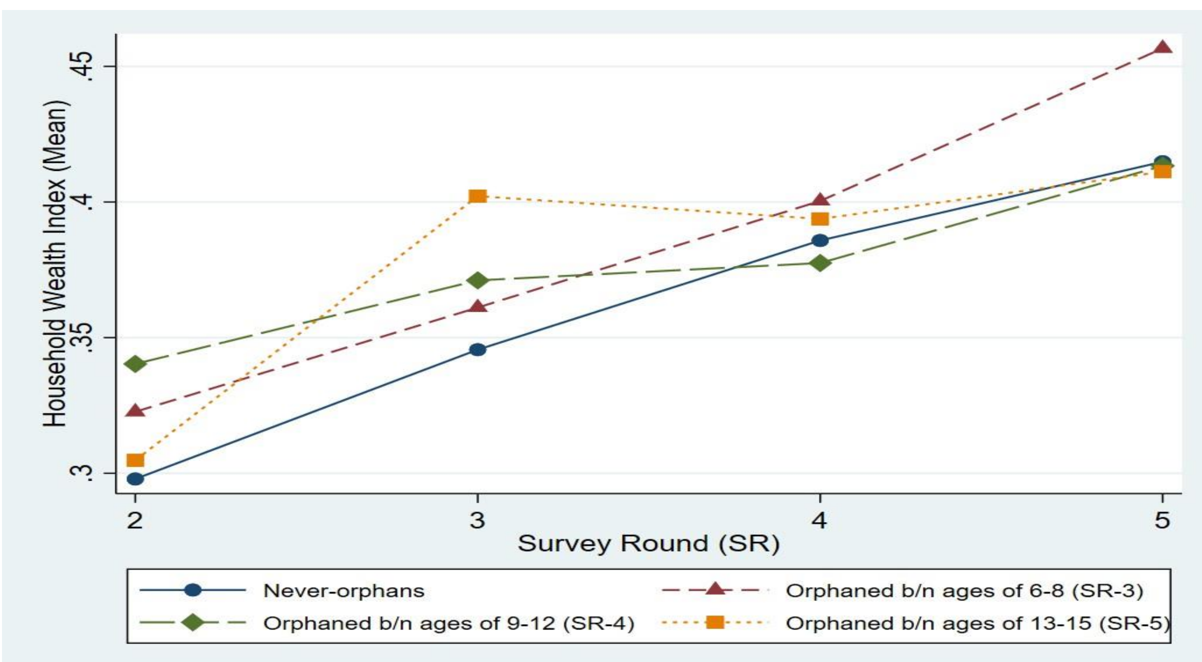

Figure A.2: Trend of household wealth index by orphanhood timing

The graph depicts the trend mean value of the wealth index of households decomposed by orphanhood timing across waves.

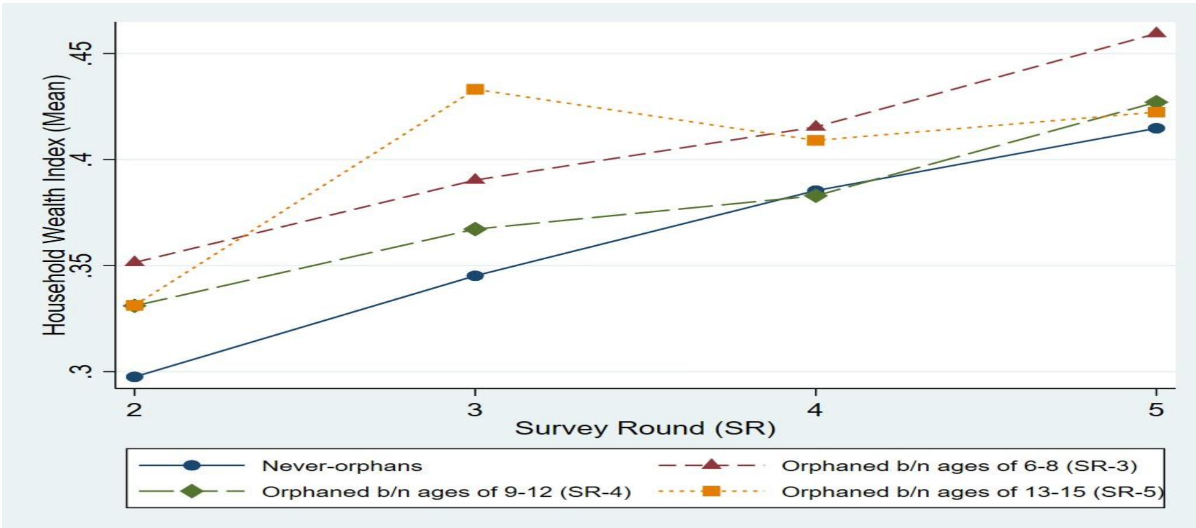

Figure A.3: Trend of household wealth index by orphanhood timing

The graph depicts the mean value trend of the wealth index of households decomposed by orphanhood timings across waves, but only for paternal orphans.

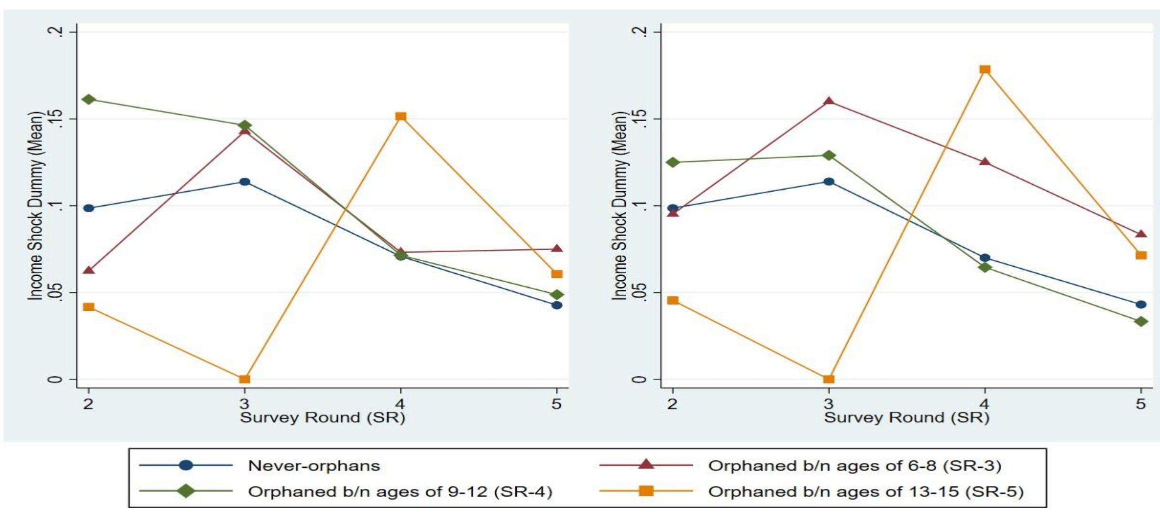

Figure A.4: Household income source shock by orphanhood timing

The graph depicts the mean value trend of the household income source shock by orphanhood timing across waves. The graph on the left shows any biological parent's death, whereas the one on the right depicts paternal death.

Chapter Five

Conclusion

Households in developing countries are exposed to significant vulnerabilities stemming from various unexpected events, which can have both immediate and lasting consequences. These adverse events in life include idiosyncratic shocks like death, illness, job loss, or asset damage, and covariate shocks like droughts, conflicts, inflation spikes, or widespread floods. Such exposure significantly affects household welfare through reduced education, labour market participation, income, and poor health outcomes. On the other hand, formal and informal insurance including social programs and networks help in mitigating the potential impact of such shocks, though access to formal insurance in developing countries is relatively low.

This dissertation aims to explore the short- and long-term association or impact of idiosyncratic shock on socio-economic outcomes such as mental health, labour market outcomes and child labour. The first paper deals with linking death of household member and loss of property with mental health contemporaneously. The second paper explores the long-term of effect of idiosyncratic shock on labour market outcomes. That is, the chapter analysis the effect of loss of parents during childhood on adult life earning and employability. The last chapter investigates the impact of parental death (orphanhood) on child labour. In the process, the contemporaneous impact of adverse event (parental death) on another adverse event (child labour) which have short- and long-term consequences on the livelihood of the victims is investigated.

The papers contribute to the development economic literature on the link between idiosyncratic shocks and socio-economic outcomes, which has received less attention. Despite the growing relevance of the problem of mental health worldwide, particularly in developing nations, there is little robust empirical research in the literature on shocks and mental health. Most previous studies consider early life covariate shocks and income shocks to study their effect on mental health problems. Previous research on early life shocks and late life outcomes also focused on covariate shocks that were linked to intermediate outcomes such as those related to education and health. There is little evidence on how early life idiosyncratic shock on parents affects their children's later life results, with most of previous research concentrating on non-labour market outcomes. In addition, the literature on the relationship between orphanhood and child labour is also limited, although there are studies that link parental death to child health and education outcomes. Therefore, this dissertation contributes to these strands of development economics literature.

Using panel data from South Africa and Ethiopia, the key findings are summarized as follows:

- There is a strong relationship between the death of a household member and mental health. Respondents who experienced the death of a household member report about

3.1% lower mental health score than those who did not experience the shock. The death of a household member due to an accident or violence and death of a close family member increases the magnitude of the coefficient. This suggests that one of the pathways by which death affects mental health is through the psychological pain of bereavement or grief. In addition, there is an evidence where death of household member correlating with income loss and thereby leading to mental health problem.

- The death of a biological father and the death of a biological mother in early childhood adversely affect wage earnings during adulthood, though the magnitude of the effect of the death of a mother is consistently higher than the death of a father. Death of a mother is also negatively related to the probability of being unemployed. Results from heterogeneity analysis show that Black South Africans who lost their father in childhood earn higher wages than the other race categories that experienced the same shock. The main mechanisms through which the death of a mother affects wage earnings are education level, perceived health, cognitive ability, and higher probability of being employed in an elementary occupation. On the other hand, only education is found explaining the link between parental death and adult labour market outcomes.

- In the relationship between parental death and child labour, parental death has a statistically significant impact on child labour. Children who have lost either of their biological parents have a 13% higher child time spent on unpaid or paid activities at home or outside of the home. Alternative estimations also show the following results: First, the cumulative effect of parental death is greater than the immediate effect, where children who are orphaned in their early years (between the ages of 6 and 8 years) are more affected than children orphaned at later ages. Second, the impact of parental death is greater at around age 12 than at earlier or later ages. Third, parental death forces children to perform unpaid household services (care and domestic work) rather than engage in economic activities (farm activities, work in family businesses, and paid work). Finally, maternal orphanhood has a greater impact on child labour than paternal orphanhood. In addition, parental death has a statistically significant and negative effect on child school enrolment and study hours but has no effect on schooling time, which seem arising due to the crowding-out effect of child labour.

The findings from the estimation results suggest the need for policy interventions and support programs to curb the short- and long-term adverse effects of idiosyncratic shocks. Specifically:

- The government can substantially reduce the effect of shocks on mental health by putting conducive policies that encourage the expansion of psychiatric and therapeutic interventions in place.

- There seems to be much room for improved welfare through expanding social support and safety nets and reducing the impact of shocks on mental health.

- There is a need for strengthening and aligning child support programmes to meet the needs of children when they are exposed to shocks. For instance, the foster child grant program, that targets children who have lost both of their parents should extend to also target children who have lost either of their parents, particularly those lost their mother.
- Support programmes should go beyond the financial grant to monitor its implementation in helping children in terms of their human capital formation. Psychological support for children should also be considered.
- The heterogenous results of the effect of idiosyncratic shocks on alternative socio-economic outcomes also necessitates case- and context-specific policy interventions and support programmes.