SCHOOL OF ECONOMICS AND MANAGEMENT

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Climatic complexity: how do early life weather shocks affect labour income?

Master's thesis by

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Abstract This dissertation explores the impact of extreme weather events during gestation and infancy on multiple outcomes, especially early labour income. The subjects are Indian children born between 1993/94 from the Young Lives longitudinal study. The weather shocks are extracted from the NOAA geo-referenced weather data. Thanks to Mediation Analysis methodology applied, not only the Direct Effects of early life weather shocks on income can be studied, but also the pathways that these shocks follow to impact income. The pathways, or *mediators*, considered here are physical and physiological health, cognitive level, educational attainment and child labour. The results suggest that suffering low temperatures in utero directly increase income at age 22 while suffering during infancy decreases it. Although there is no Direct Effect of rainfall shocks on income, it is observed that these have profound Indirect Effects on children's outcomes, primarily through the educational attainment and child labour mediators. In addition, multiple differential effects by gender, trimester of gestation and season of the year are provided to enhance the understanding of these effects. The evidence is robust to changes in the definition of weather shocks.

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Para Papá, por todo.
Ojala poder llevar una vida tan plena como la tuya.

$$\triangle x \triangle p \geq \frac{h}{4\pi}$$

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1. Introduction

In a world expecting significant climate changes in a short period, understanding and quantifying how climate affects humans is vital. However, not everyone would be affected equally. The standard wealth, income, gender and regional inequalities also apply to climate consequences on people. Individuals in poorer and agriculture-dependent countries would undoubtedly suffer more from the upcoming climate change and the consequent increase in extreme weather events, like floods or heat waves.

This dissertation scope is centred on another perspective for the unequal impact of climate on humans: age. Children's vulnerability undermines their capacity to cope with weather events in early life, bearing the most significant shocks. Studying this population subgroup is a vital research endeavour, even more so knowing the grim climatic future. Children born between the end of the last century and the beginning of the 21st century will live lives with significant climatic changes, both in the long- and the short term.

The analysis presented here aims at measuring exposure to extreme weather events during gestation and infancy (up to age 1) to observe outcomes shortly after the individual has become an adult. It is focused on the critical crossroad between childhood and early adulthood. This crucial period is often neglected in the literature that addresses climate effects on socioeconomic outcomes.

The purpose is to measure these hypothetical climate effects on early labour market outcomes. The hypothesis is that children who have suffered more environmental shocks have worse wages since the beginning of their working careers than those who were less exposed to extreme weather events. The main reason to focus on early labour market outcomes is that they summarise the children's previous educational and health history. They also represent the first milestone for the individual's future as an independent adult. Worse wages at the beginning could mean worse wages later in the professional career. Formally:

Question 1 *Does climate have an impact on income? More specifically, do early-life extreme weather events affect young adults' labour income?*

The follow-up question is evident: *how* environmental shocks affect labour outcomes? Thanks to the Mediation Analysis approach applied in this work, this question can be explored. This dissertation considers multiple possible mediators based on previous research: physical and psychological health, cognitive results and education. Child labour decisions are included as an additional mediator, which the literature has not previously considered. These intermediate outcomes are measured at different times of childhood and youthhood. Thus, the second question is left as:

Question 2 *Through which pathways does exposure to extreme weather events in early life affect young adults' labour income?*

The contributions of this dissertation are many. First, it studies how early-life climate shocks affect individuals from childhood to adulthood. This knowledge will be most helpful in a world where the climate will be increasingly harsher. Secondly, it explores plausible mechanisms through which climate affects people. One of these mechanism is early child labour, a mediator often neglected in the literature. The information extracted here helps policymakers implement better strategies, especially those aimed at reducing climate damage to children. Third, labour market outcomes are measured in early adulthood. Then, we can observe the medium-term effects of climate on children, while most studies focus on incomes later, usually at mid-life. It represents an opportunity to observe when the scarring effects of climate appear. Fourth, the Mediation Analysis methodology used here has not been applied before in studies similar to this dissertation. Lastly, the analysis is performed using the Young Lives study, which provides several insights into the life course of Indian children. To my knowledge, no other study that measures climate exposure in early life has used this study.

The dissertation goes as follows. The second chapter introduces the relevant theory and the multiple strands of literature needed to understand this complex phenomenon. The third chapter introduces the socioeconomic and geo-referenced weather data, and the Mediator Analysis methodology applied. The fourth chapter presents the results and a series of relevant comments. Chapter five provides robustness checks. The sixth chapter discusses the results and the limitations of this dissertation. Finally, chapter seven concludes.

2. Literature Review

2.1 Theoretical background

Human bodies have memory. Circumstances that happen at some point in our lives can be reflected in later circumstances and outcomes. In this introductory part of the literature review, the principal theories that address how previous situations influence current statuses are reported. These are the theoretical frameworks upon which this dissertation is built.

This literature stems from epidemiological sciences. Therefore, many of the ideas are framed in medical terms. Nonetheless, as will be seen, these models have also been applied in Economics to measure various socioeconomic statuses. These types of models are often referred to as "life-course models". Distant factors matter, but proximate circumstances are also equally determinant. These life-course models are divided between those that stress more the importance of the first factors and those that emphasise the second (Montez and Hayward, 2011).

The "Pathway framework" assumes that, although important, the early life conditions are not entirely determinant. Instead, multiple proximate situations influence to a greater extent the adulthood outcomes. Exposures during childhood set the individual into a "pathway" (hence the name) that explains the situations later in life. In short, each proximate situation comes from previous proximate situations, which ultimately come from an initial exposure (Montez and Hayward, 2011). In a classic example, children coming from lower socioeconomic backgrounds have more chances to smoke, perform less physical activity, access to social nets, etc., which turns into greater mortality rates (Ross and Wu, 1995). The *accumulation* of these factors is what increases the risk, not the childhood poverty (Ben-Shlomo and Kuh, 2002).

In contrast, the "Biological Imprint framework" hypothesise that there are moments in life where being exposed to something has long-lasting consequences: a "biological imprint" (hence the name) on the individual's body. The term "critical period" defines these life stages and underlines the irreversibility of the exposures that happen during them. In turn, the "Pathway framework" would deem these periods as "sensitive": influential, but not decisive (Montez and Hayward, 2011).

Intuitively, the more at the beginning of life, the more crucial the stage becomes, as individuals are weaker and less developed [1]. Then, the gestation and infancy stages might be considered the most crucial periods. Worse environments this early in life are translated into worse health and socioeconomic outcomes later. Negative shocks that happen in utero and lead to undernourishment or mother's illnesses are reflected in all sorts of child outcomes. This specific Biological Imprint model

[1] Although this is not always true, see (Dean and Kurtzke, 1971) for a counterexample.

is known as the “fetal origins hypothesis” (Almond and Currie, 2011; Barker and Osmond, 1986; Barker, 2001; Saulnier and Brolin, 2015).

This hypothesis has been tested on a multitude of shocks like civil wars, famines and pandemics, finding significant effects on the physical and psychological health and a multitude of socioeconomic outcomes (Alderman et al., 2006; Almond, 2006; Kertes et al., 2017; Lindeboom et al., 2010; Palloni, 2006; Van Os and Selten, 1998; Walder et al., 2014). This extreme vulnerability is extended until the beginning of the weaning period [2]. Then, it decreases progressively up to the time the child can support himself/herself (Bengtsson et al., 2004).

This dissertation applies the fetal origins hypothesis. It deems the in utero and infancy stages as critical periods for exposure to climate shocks. It suggests that extreme weather events in early life have long-lasting consequences. However, this dissertation combines both approaches instead of being entirely within the Biological Imprint framework and rejecting the Pathway one. This combination is often described as “Cumulative framework” (Montez and Hayward, 2011). Figure 2.1 depicts a classical diagram to represent these three models. In case (3), there is a permanent imprint of early life exposures, but this is altered by other adult exposures that also act as mediators. This dissertation uses a methodological strategy, explained in Chapter 3, conceptually close to the Cumulative framework.

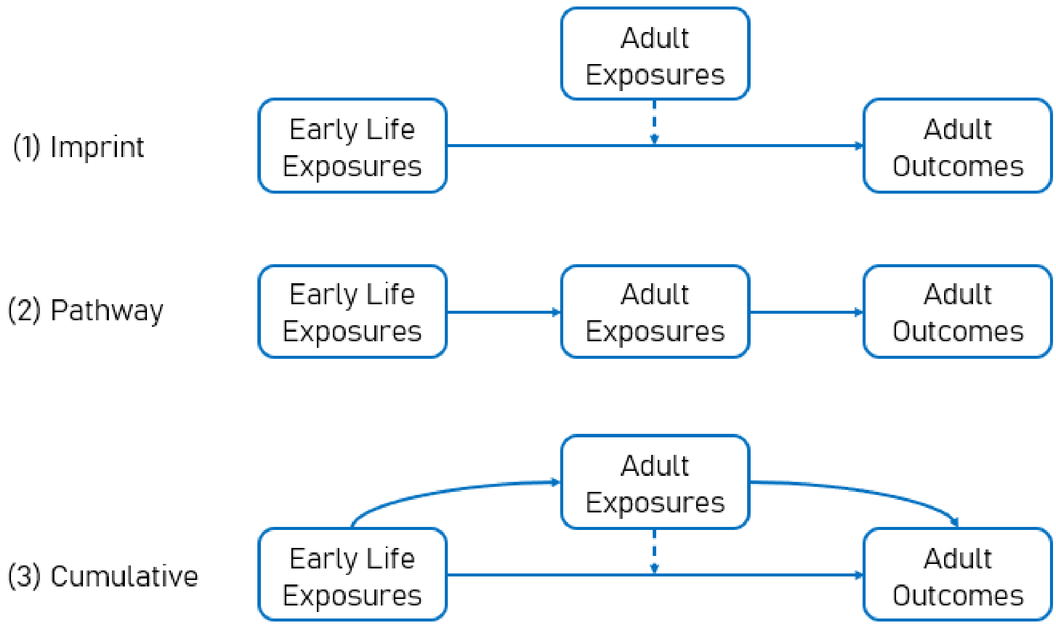

Figure 2.1: ***Different life-course models***

Source: adapted from Montez and Hayward (2011) and Berkman (2009)

Before exploring the literature related to this analysis, some additional life-course terminology needs to be addressed. Preston et al. (1998) did a phenomenal work outlining the different effects that early life exposures might have on the individual (Montez and Hayward, 2011). For this dissertation, 2 of the four effects are

[2]The human breastfeeding period last between 1 and 2 years, depending mainly from regional traditions (Whitehead, 1985).

important[3]:

- Scarring effect: survivors of adverse shocks in early life are more vulnerable to other adverse shocks later in life, as the initial shock undermined their correct development.

- Selection effect: after an adverse shock, the weakest individuals might have perished, leaving the most robust ones.

The interplay of these two is crucial. A typical empirical consequence of the selection effect is that adverse shocks appear to have *positive* impact on adult outcomes, especially if the outcome is related to physical health. However, if the scarring one is strong, the two effects could cancel each other out.

2.2 Previous research

The scientific consensus about a man-made climatic change was formed around the 1980s, aided by seminal works, such as Hansen et al. (1981), and the later establishment of the Intergovernmental Panel of Climate Change (IPCC). In Economics, founding articles warned about the negative effect of increasing temperatures on growth and how they could provoke significant changes in the economy (Mendelsohn et al., 1994; Nordhaus, 1991). Partnering with health experts, other economists, like Dockery et al. (1993), saw that more pollution led to higher mortality. What was the beginning of Climate Economics has resulted in economists from all fields trying to measure the effects of climate and climate change on virtually every socioeconomic variable. Being a cross-disciplinary field, this has led to economists using climatic data and models wrong in many cases (Auffhammer et al., 2020). Nevertheless, today we have gathered much information about the climate impact on societies.

This literature review analyses some of the articles relevant to this dissertation that have helped move the field forward. First, it overlooks the macroeconomic impacts of climate. Second, it moves to a microeconomic perspective, studying how households respond to extreme weather events. Finally, as they are the main subjects of this dissertation, it will focus on how climate impacts children physically, psychologically and labour-wise. It will have a partial focus on India, as it is the country where the analysis of this dissertation is set.

Macro perspectives

Climate has a proven effect on economic output and productivity. On average, warmer countries have lower income (Dell et al., 2009) and productivity (Deryugina and Hsiang, 2014), with temporary increases in temperature affecting income more than long-run climatic variations. This effect would be explained mainly through adaptation, according to Dell et al. (2009). However, communities have fewer resources to cope with the worsening climate in poorer countries. Therefore, adaptation here is lower and climate adverse effects on output and growth rates greater, impacting agricultural and industrial outcomes (Dell et al., 2012). Dell and co-authors also observe that political instability is higher in warmer years, evidence

[3]The other two, immunity and correlated environments effects, applied more for biological settings like the study of mortality determinants.

that is confirmed by Hsiang et al. (2013) who, in an extensive review, established that higher temperatures increase the risk of civil war, local conflict and antisocial behaviour.

In developing countries, *to grow* would not even be a simple solution to escape the climate's grip. Initial increases in income could elevate the exposure to climatic disasters due to behavioural changes such as house location choices (Kellenberg and Mobarak, 2008). Although surpassing certain levels of income decrease climatic exposure, even the wealthiest economies "feel the weather". In the US, hot working days (above 30ºC) cost counties 20$ per person. Even at lower temperatures (above 15ºC), 1ºC more reduces productivity by 1.7% (Deryugina and Hsiang, 2014).

Developing countries will bear most of the impacts of climate change. Since one of the primary sources of income in these countries comes from agriculture, any climatic shock that reduces agricultural output will produce food shortages and rapidly transform into an income shock. In short, climate change will increase poverty in emerging countries mainly through the agriculture mechanism (Hertel and Rosch, 2010). In tropical or arid regions, where most developing countries are located (Dell et al., 2009), higher temperatures in the following decades will reduce agricultural output since the beginning (Tubiello and Rosenzweig, 2008). In India and Brazil, two counties with good agricultural data, even slight temperature increases will reduce net revenues and land value, respectively (Mendelsohn, 2009). In addition, results show significant geographical heterogeneities, depending on regional climates, type of soil, amount of people engaged in agriculture and orography. This implies that some regions will benefit marginally from weather changes, while others will get hit severely, with the pertinent consequences on inequality and internal displacements.

Micro perspectives

The macroeconomic impacts of climate will come through aggregated microeconomic (negative) experiences. Households and people will have to adapt to the extent that their resources reach. There is no surprise in saying that poorer households will bear the most significant blow from climate change.

Again, the key is agriculture. Because extreme weather events reduce income from that sector, rural households have more difficulties smoothing consumption when these shocks arrive. In a context of high seasonality induced by agricultural activities, this dramatically reduces the survival chances of these households (Chaudhuri and Paxson, 2001) leading to higher poverty rates (Dercon, 2006). In agrarian societies, to possess land is a synonym for wealth (Bhalotra and Heady, 2003). If (low) wealth is a large predictor of a household's vulnerability to agricultural shock induced by climate (Giné et al., 2008), climate change will create a vicious circle where poor households always suffer from climate, with the richer ones being further and further away. In a very influential work, Binswanger and Rosenzweig (1993) showed that, in India, unexpected changes in rainfall affected the poorest households by reducing 35% their agricultural profits, whereas the wealthiest households were unaltered.

Poorer households bear most of the impact of climate change and disasters. It makes the individuals living in them more prone to suffer harsher situations or make difficult decisions. How the households buffer the environmental shock depends on many factors. In rural societies, after spending the assets or selling them, as in the case of livestock, households have to rely on external help (Acosta et al., 2021;

Bengtsson et al., 2004). A traditional solution comes from having access to credit markets (Beegle et al., 2006). However, these function inefficiently in developing countries, and often the household ends up in a worse situation if the economic stress situation continues and is unable to repay the high-interest rates of the loans (Besley, 1994). If no help coming from other social nets is received, the household would have to either change its labour supply, reallocate consumption or postpone it (Bengtsson et al., 2004).

When the household's assets are drained off, and the rest of the possibilities are exhausted, the direct consequence is food insecurity, which is rapidly transformed into illnesses (Pells, 2011) and higher mortality, especially between the 1 and 9 years old cohort (Ezra and Kiros, 2000). In addition, households that suffered food insecurity in the past do not rebound and are more likely to suffer it in the future (Dornan et al., 2014). This reinforces the climate change-poverty vicious circle commented on before. Lastly, when the situation turns unacceptable, many households are forced to migrate, choosing between a bad and a worse situation. Climate change might reduce household assets to the extent that migration, which is costly, ceases to be an option. However, if the household stays, it may be more vulnerable, reducing the assets and increasing the poverty further (Kaczan and Orgill-Meyer, 2020).

Climate impacts on children

The individuals of any household can be divided between those who are net producers and those who are net consumers. In rural societies, this division is more important than in industrial countries, with children lying in the net consumer category (Bengtsson et al., 2004). Thus, they depend on others (their caregivers) to survive, especially when difficulties arrive in the household. For that reason, children in developing countries are one of the risk groups more vulnerable to any shock, including weather ones. Climate disasters often occur in developing countries, where social safety nets are thin. Given that the children to adult ratio are high in these countries, children will disproportionately suffer more (Hanna and Oliva, 2016). Nevertheless, how exactly are children affected by climate?

To start, children in developing countries will have more diseases as a cause of climate change due to more hot days, water shortages and heavy rainfall illnesses, like cholera (Orlowsky and Seneviratne, 2012). In general, most studies observe that children are very vulnerable to heat-related deaths linked to malaria and respiratory and gastrointestinal diseases (Xu et al., 2012). In lower-income countries, more than a third of children's deaths below 14 years old are attributable to climate (Bartlett, 2008). Moreover, these figures do not tell us about the loss of healthy years, which, if accounted for, could increase the real burden of climate on children (Pruss-Ustun et al., 2006). Sheffield and Landrigan (2011) comment that up to 88% of all disease burden of climate is concentrated among below-5-year-old children. Additionally, women represent an even more vulnerable subgroup, as female infant mortality is more sensitive to income shocks than the male one (Baird et al., 2011), even though males at early stages are more fragile than females (Kraemer, 2000). This is consistent with the fact that boys are often favoured over girls in developing countries when households experience difficulties (Dreze and Sen, 1990).

Climate also has profound psychological effects on children. Clayton et al. (2017) did an excellent review about this psychological burden and how to prevent it.

Fatalism, helplessness, PTSD, anxiety, sleep disorders or memory loss are common issues displayed by children that have suffered climate shocks. If not appropriately treated, cognitive deficits and behavioural problems appear (Burke et al., 2018), which may affect education and labour market outcomes later in life.

Climate shocks in early life

However, what happens when the climate shock occurs during the gestation period or the first years of life? That question can be answered with the theories explained at the beginning of this chapter. Because this dissertation is centred on very early life climatic shocks (gestation and infancy), the fetal origins hypothesis can be applied (Almond and Currie, 2011; Barker and Osmond, 1986; Barker, 2001; Saulnier and Brolin, 2015).

There is evidence that early life weather shocks have scarring effects on children. On the one hand, suffering extreme weather events in utero is linked to having more of the psychological disorders cited above (Burke et al., 2018). Regarding socioeconomic outcomes, in a study in Indonesia, Maccini and Yang (2009) found that women that had more early rainfall (i.e., in utero and during the first year of life) have today better health, height, schooling and assets. However, these effects were not found in men. Maccini and Yang (2009) conclude that the mechanism underlying their investigation is that more rainfall increases crop output, resulting in more food and income in rural households, which is translated into better infant health. Lastly, healthier children can bring out the full potential of their education, which explains better socioeconomic outcomes.

A similar result is found in Shah and Steinberg (2017), where positive rainfall shocks (i.e., months with rainfall accumulation above the 80$^{\text{th}}$ percentile) in utero and until age 2 seem to increase educational outcomes. However, the authors observe different short-term effects: the same educational outcomes are reduced if the positive rainfall shocks happen when the child can perform work. Shah and Steinberg (2017) attribute this differential effect to the increased opportunity cost of schooling in good agricultural years. When agricultural wages increase, the children tend to work more.

But too much rainfall has a reverse effect. In Ecuador, flood exposure during the first trimester of gestation is negatively correlated with children's height and cognitive test outcomes, which is partially explained by the reduction in household consumption and income (Rosales-Rueda, 2018). In Nepal, children who experience abnormally wet monsoons have lower weight during their first years. There is a negative effect on height, but catch-up growth is sufficient to make it disappear by age five (Tiwari et al., 2017). However, in Mexico, there is persistence after some years: children who suffered extreme El Niño rainfalls in early life have worse anthropometric and cognitive results (Aguilar and Vicarelli, 2011).

The same results appear for the reverse. Alderman et al. (2006) acknowledged the critical role of drought shocks in Zimbabwe in explaining children's and teenagers' health. This idea has been later extended by Hyland and Russ (2019), who aggregates several sub-Saharan DHS in their analysis. They observe that women exposed to drought in early life are today shorter and less wealthy and educated. Furthermore, they establish that the children of those women are underweight, which may be a possible mechanism for the intergenerational transmission of environmental shocks.

Lastly, not only rainfall is essential, but temperature shocks also play a crucial role in children's correct development (Zivin and Shrader, 2016). In the US, fetuses that experienced high temperatures in utero are more likely to have a reduced weight-for-age (Deschênes et al., 2009). Also in the US, one more day above 32ºC from gestation to the first year of the child represents a 0.1% reduction in adult annual earning (Isen et al., 2017). The significance of these results is wiped out if the household used air-conditioning. In a developing country like Ecuador, adults who experience in utero 1ºC above the average have 0.7% less income (Fishman et al., 2019). Compared to those that study rainfall shocks, the improvement in these articles is that they use actual earnings instead of wealth indexes that proxy income through household assets.

Shocks, education and child labour

After a shock, the household goes through a period of restructuring. The decisions aimed at recovering the lost level of food intake, assets or general welfare are various, as we have seen (Bengtsson et al., 2004). In developing countries, school fees are left unpaid, or children are often forced to work. These situations, education and child labour, are critical for this dissertation since they are possible mediators of the children's first labour outcomes. Before anything else, we have to acknowledge that although child labour is morally unacceptable, families usually do not have other options for sustaining the household (Basu and Van, 1998). For example, in Tanzania, accidental crop losses lead to more child labour, especially in those households with small agricultural properties (Beegle et al., 2006).

First, it is commonly assumed that child labour displaces school (Baland and Robinson, 2000). However, they are not perfectly time substitutes. In Ghana, one hour of child labour reduces the time allocated to the school by 0.38 hours (Boozer and Suri, 2001), which implies that most children are both working and going to school. Nevertheless, these have obvious consequences for the level of educational attainment. Also, in Ghana, children that work display less mathematical and reading skills (Heady, 2003). This is because there is less school attendance and working children are more tired and unmotivated with their studies. Studies in Latin America have also found that child labour increases the chances of course repetition (Patrinos and Psacharopoulos, 1997) and, again, decreases school attainment (Gunnarsson et al., 2006). On the other hand, studies in Cambodia have not found that child labour is a predictor for early school dropout (No et al., 2012, 2016).

The relationship between this decrease in education due to child labour and later earnings is not straightforward. In a study in Vietnam, children that work were found to have more probability of wage work when adults (Beegle et al., 2009). The authors state that *"some of the negative effects of foregone schooling could be offset by the benefits of the earlier work experience as a child"* (Beegle et al., 2009, p.887). However, the time at which the child starts to work is crucial. Using Brazilian data, Emerson and Souza (2011) found that child labour before adolescence is harmful to later earnings. However, starting working around 13 years old and after is slightly positive. In the same country, starting before this age results in an increased likelihood of belonging to the two worst income quintiles (Ilahi et al., 2000). The reasons behind this non-linear relation are explained in Gunnarsson et al. (2006, p.33). First, very young children that are very tired because of labour might not be able to learn efficiently. Second, this tiredness makes them injury-prone, which may reduce their school attendance. Lastly, and most interesting, work and school might be complementary after basic skills are acquired, but they might be substitutes before learning them (i.e., during primary school).

Youth employment in developing countries

This last part of the literature review addresses the complexity of labour markets in developing countries and the difficulties young adults have when looking for their first professional experiences.

The initial models that described labour markets in developing countries as highly imperfect (Harris and Todaro, 1970; Lewis, 1954) were contested during the 1980s with various empirical studies (Blau, 1985). Testing a theoretical model against real microdata, Rosenzweig (1980) found that rural labour markets in India tend to have more neoclassical "efficiency properties" than initially thought. Assumptions like an exogenously fixed wage rate or a demand-driven labour market, deemed detrimental, were not observed.

Nevertheless, labour markets in developing countries have some apparent deficiencies. Among the clearest are the low earning levels and the long working days (Fields, 2011). In addition, jobs that offer regular wages, or wages alone, are very scarce, with a large majority doing casual employment, self-employment and unpaid activities (Fox and Kaul, 2018). Therefore, income uncertainty is also a characteristic of labour markets in developing countries (Fields, 2011).

Education is not always the escape towards these desired stable jobs. Although returns to education are high in developing countries (O'Higgins, 2003; Psacharopoulos and Patrinos, 2002), these returns do not appear immediately. The odds of being unemployed during early adulthood are higher among those better educated, those who belong to wealthy households and those who live in urban areas (Fares et al., 2006; Van der Geest, 2010). Furthermore, many of these young individuals are often unpaid or low paid (Msigwa and Kipesha, 2013).

India is one of the countries where the employment gap between the youth and adults is higher (Van der Geest, 2010), a sign of the difficulties for young people to enter the labour market discussed above. Van der Geest (2010) explains that part of this extremely high Indian youth unemployment might be explained due to a land scarcity problem. In land-abundant areas, the youth will work on their family's land if other types of jobs do not appear. However, in land-scarce areas, like India, that option is less available, as not every family possesses land.

On another note, women have to face even more challenges to obtain good jobs. In developing countries, they are often confined to do informal activities, which makes them more prone to labour abuses (Chant and Pedwell, 2008; Fields, 2011). In India, the female labour force participation was only 26% in 2019, and around 50% of young women were neither working nor in education, figures among the lowest in the world. The reasons behind such poor values are diverse, but the main ones are cultural norms against female employment, which impedes educational progress and the possibility of doing outdoor work for women (Dean and Jayachandran, 2019; Van der Geest, 2010).

3. Empirical Strategy

3.1 Data

The Young Lives study

The motivation of this dissertation is to quantify the effect of early life Extreme Weather Events (hereafter EWE) on children and see how they are translated into early labour market outcomes. Recall the two main questions proposed in the Introduction. Question 1 inquires if the *early life extreme weather events affect young adults' labour income*. Then, Question 2 tries to disentangle *through which pathways does exposure to extreme weather events in early life affect young adults' labour income?*.

To accomplish this, a database that combines extensive information about the life course of children is needed. For that reason, this dissertation uses the Young Lives study (hereafter YL) (Boyden, 2018; Huttly and Jones, 2014; YL, 2022). This longitudinal project follows children and their families in four developing countries (Ethiopia, India, Peru and Vietnam). The YL contains very fine-grained information on virtually every dimension of a child's life: anthropometric measures, educational outcomes, community infrastructure, descriptions of the household's assets, etc. [1].

It consists of two cohorts that were first interviewed in 2002. The Younger Cohort was one year old, while the Older Cohort had eight years old. These children were questioned at intervals of 3 to 4 years. Round 1 was completed in 2002, Round 2 in 2007, Round 3 in 2009, Round 4 in 2013 and Round 5 in 2017. Across these rounds, the YL has acknowledged the changes in the lives of the children as they grew up. In the final rounds, for example, data about marriages and income were included [2].

Because of the Covid-19 pandemic, Round 6, scheduled for 2020, was made through telephone calls instead of the traditional face-to-face interviews. Since it has a different structure and asks different questions due to the Covid situation, this dissertation only considers the information up to Round 5. As the objective is to study differences in labour market outcomes, the Younger Cohort is not considered, as of Round 5, the children were only 16 years old. The individuals considered for

[1] The YL also has information about the different climatic shocks (e.g., droughts or floods) suffered by the household where the YL children live. This is an exciting characteristic of the YL study, as not many databases contain information about climate shocks and children (Hanna and Oliva, 2016). Although related to this dissertation, this information is not considered, as it is interested in early life weather shocks.

[2] Briones (2018) reconstructed the information between rounds. This "reconstructed" file has been the empirical basis of this dissertation. However, it mainly contains essential variables. For that reason, that information has been complemented with variables coming from the raw datasets, like the labour income of the YL children (Huttly and Jones, 2014).

analysis in this dissertation are the children of the Older Cohort, those who were 8 in 2002 and 22 in 2017.

Instead of using the four countries cited above, this analysis focuses only on India. First of all, this is done to eliminate the heterogeneity between countries. Children in Ethiopia, India, Peru and Vietnam can share a common "climate history" (i.e., most had suffered droughts and floods), but their cultural, institutional and labour market backgrounds are completely different. Peru and Ethiopia were not considered due to sampling deficiencies [3].

That left Vietnam and India as candidates. Both had similar rates of attrition and number of children in Round 5. After a preliminary analysis, India was selected. First, the YL project in India only considers the Andhra Pradesh and Telangana states [4], which permits a more geographically concrete analysis. Second, the more dispersed spatial distribution of villages in India would provide more variability in the temperature and precipitation data, a crucial element of the analysis. Third, from this preliminary analysis, it seemed like the Indian YL children had suffered more climate shocks than Vietnamese ones, with more marked wealth differences between those that had suffered and those who did not.

The Young Lives study in India

The Older Cohort sample of the Young Lives study in India counted in Round 1 with 1008 children. This number had been reduced to 914 by Round 5, an attrition percentage of 9.3%. Although this represents a sizeable part of the original sample, the essential characteristics (gender, caste, maternal education, wealth index and urban rates proportions) were not altered (YL, 2017).

The YL was intended to be a regionally representative study rather than a national one. The sampling method followed a semi-purposive technique. This is based on the sentinel site procedure of the Demographic and Health Surveys (DHS). Each sentinel site was "designed" to represent a certain socioeconomic reality in Andhra Pradesh. A total of 20 different types of sentinel sites were created to cover all the spectrum (YL, 2017).

The next step was to select actual locations to match those sentinel sites. First, of all the 23 districts in Andhra Pradesh, seven were selected based on various socioeconomic variables. In India, each district is composed of *mandals*[5]. In the districts selected, 20 mandals were chosen based on the predetermined characteristics of the 20 sentinel sites. Finally, 50 children were selected from each mandal, all from 50 different households (YL, 2017).

Although this sampling design does not have the statistical power of complete randomization, the results are satisfactory. A comparison with the more representative DHS observed that much of the socioeconomic characteristics of the two samples were similar. However, the YL seemed to be a pro-rich study: its households had

[3]Peru was discarded first since the number of children for the Older Cohort in Round 1 was lesser than their counterparts (N=714). Ethiopia had the same problem, but for Round 5. Also, the attrition level in the African nation was larger. See here the survey design and sampling briefings for Ethiopia (YL, 2018*a*), India (YL, 2017), Peru (YL, 2018*b*) and Vietnam (YL, 2018*c*).

[4]These two states were only one up to 2014, the moment in which Telangana gained its independence from Andhra Pradesh.

[5]On average, each mandal comprises around 20-40 villages, with each village containing a few smaller hamlets.

better access to services and slightly more assets than those households in the DHS (Kumra, 2008). This induces some biases in this dissertation. Assuming that poorer households and children suffer more from climate shocks, the results shown in this dissertation could represent a lower bound of the actual effect.

Weather data

We need climatic data to determine how many EWE the children of the YL suffered. This dissertation does not aim to measure the impacts of some particular environmental disaster. It instead looks for continuous exposure to EWE. Concretely, exceptionally dry or wet months for rainfall and exceptionally warm or cold months for air temperature. The geo-referenced climatic data comes from the University of Delaware Air Temperature & Precipitation database (UDel hereafter) (Willmott and Matsuura, 2001). It covers monthly mean temperatures and total rainfall from 1900 to 2017 (in their last 5.01 version). It has a spatial grid of 0.5-degree latitude x 0.5-degree longitude grid, which corresponds to "pixels" of roughly 50x50 km^2 at the equator [6].

Where the YL children live?

The states of Andhra Pradesh and Telangana occupy the central-southeastern area of the Indian Deccan Plateau. Geographically speaking, they can be divided into three agro-climatic regions, as Figure 3.1 reflects. Coastal Andhra and Rayalaseema represent the modern Andhra Pradesh state (YL, 2017).

The central part of Coastal Andhra consists of a large basin, very productive agricultural-wise, created by the joint forces of the Krishna and Godavari rivers. It is not for nothing that Andhra Pradesh is called the "rice bowl" of India (Samarpitha et al., 2016). The more the southwest we move, the less rainfall the soil receives. This creates a semiarid climate in the Rayalaseema region. This regional division will be taken into consideration in Chapter 4, which applies Regional Fixed Effects. Figure 3.2 gives the reader a visual idea of the UDel database and the weather distribution in Andhra Pradesh.

Socioeconomically speaking, the undivided Andhra Pradesh has one of the lowest poverty rates in India (21% in 2011) and has been one of the fastest in reducing this percentage since the 90s. On the other hand, income inequality is still high compared to other states, especially in urban areas (Panagariya and Mukim, 2014). Andhra Pradesh seems to be a fast-moving state that is experiencing the rising inequality that often happens when income rises (Kuznets, 1955). The International Labour Organization, in its 2018 report about wages in India, outlines several insights for Andhra Pradesh. In terms of income per capita, it has the closest value to the average of India, only 7 pp above it.

Regarding wages, the state presents some imbalances. Wages for casual workers are around the country average. However, regular workers receive a much-reduced wage compared to the country's average. Still, casual workers are paid between

[6] There are databases with higher resolution, for example, 0.25-degree latitude x 0.25-degree longitude grid. However, the UDel database was chosen since data from 1963 was needed. Not every climatology source covers this period. Additionally, this database is often used in papers that study climate impacts on society like Hyland and Russ (2019); Maccini and Yang (2009). See Auffhammer et al. (2020) for a review of other possible gridded climate databases.

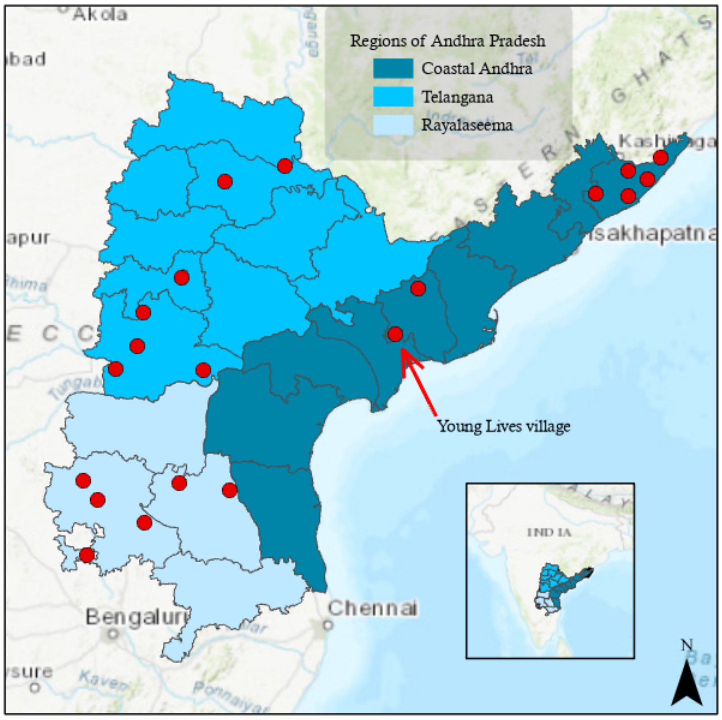

Figure 3.1: ***Agro-climatic division in the undivided Andhra Pradesh***

Source: self-elaboration based on Young Lives data (Boyden, 2018; Huttly and Jones, 2014; YL, 2017). *Note*: the coordinates of the YL villages are not provided in order to guarantee anonymity. Nevertheless, the sampling report of each country provides an approximate location (YL, 2017)

two and three times less than regular workers, and those in urban areas are paid almost 70% more than those in rural areas (ILO, 2018). Finally, this state has been subjected to violent episodes coming from the Naxalite movement (Mohanty, 2006).

3.2 Methodology

The objective is to complete a comprehensive profile of how weather shocks in early life affect children's later life outcomes, with a special focus on early labour income. To achieve this, the overarching methodology followed by this dissertation would be a Mediation Analysis (also known as path analysis). Concretely, the product method approach. This framework was popularized in the very influential article of Baron and Kenny (1986), although it was proposed earlier (VanderWeele, 2016). In essence, this methodology accounts for the possibility that the direction of causation might be split into a *Direct* and an *Indirect* Effect. Suppose that you have an outcome Y of individual i, who has been subject to an exposure X. Non-Mediation Analyses observe the effect of X on Y, which can be called a "total effect". This basic approach may be able to answer Question 1, *but not Question 2*.

Thus, a Mediation Analysis is useful to find the different paths that X follows to affect Y. With it, this dissertation can answer Question 2. All is centred on the idea that a mediator outcome M, or sets of mediators as this dissertation proposes, is also affected by X, while at the same time affecting Y. This effect of X on Y through

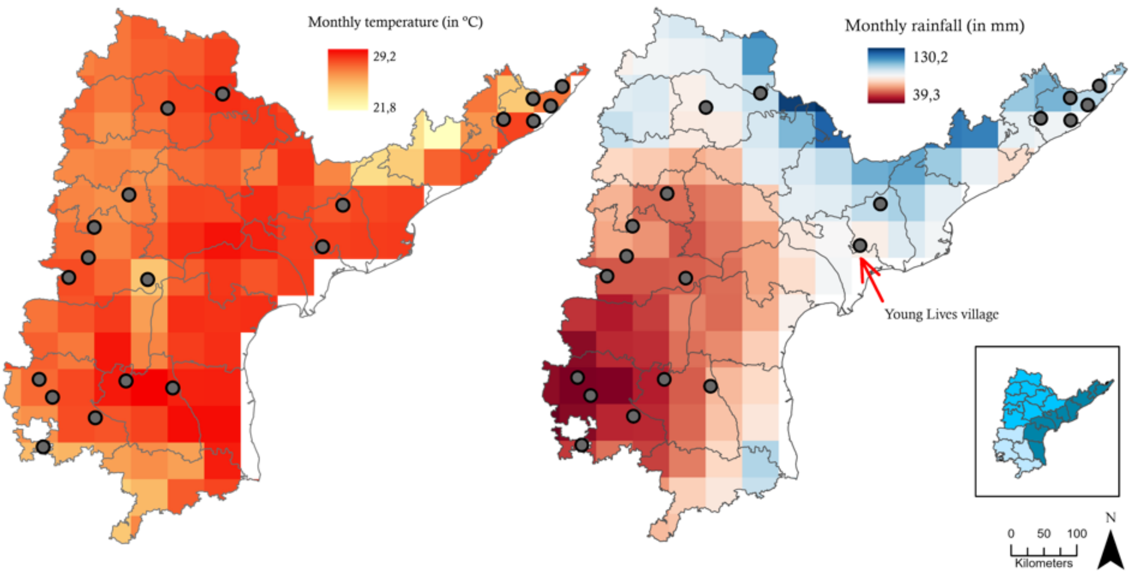

Figure 3.2: ***Monthly weather averages in undivided Andhra Pradesh, 1963-1992***

Source: self-elaboration

Note: figure reads as: the area with a mean monthly rainfall of 130.2 mm, had a mean annual precipitation of 1562.4 over the period 1963-1992.

M is called the "Indirect Effect". A conceptual depiction of the Mediation Analysis is represented in Figure 3.3. One can see the resemblance with the life-course model (3) presented in Figure 2.1.

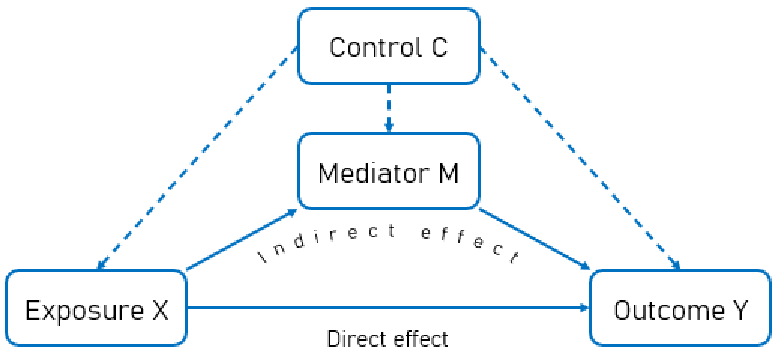

Figure 3.3: ***Conceptual approach to Mediation Analysis***

Source: self-elaboration

This basic framework can be applied with different specifications [7]. This analysis considers the product method, which is a deviation from the classical method of Mediation Analysis that can also be applied to non-linear variables (VanderWeele, 2016), as is the case with the logarithm of the total income, the primary outcome

[7] Check VanderWeele (2016) for a light revision and VanderWeele (2015) for a more thorough one of all the possibilities and literature within the Mediation Analysis.

of interest. Formally, we first regress the outcome of interest Y on the exposure X, the mediator M and a set of controls C:

$$E[Y|X,M,C] = \theta_0 + \theta_1 X + \theta_2 M + \theta_3^{'} C \tag{3.1}$$

Then, we observe how the mediator M is affected by the exposure X and the set of controls C:

$$E[M|X,C] = \beta_0 + \beta_1 X + \beta_2^{'} C \tag{3.2}$$

The total effect TE is the addition of the direct effect DE and the indirect effect IE, which for the product method followed in this dissertation is left as follows:

$$TE = DE + IE = \theta_1 + \beta_1 \theta_2 \tag{3.3}$$

Combining equation 3.3 with Figure 3.3, θ_1 would be the arrow going from Exposure X to Outcome Y. Then, β_1 is the arrow going from Exposure X to Mediator M. Finally, θ_2 is the arrow going from Mediator M to Outcome Y.

The Mediation Analysis approach is designed to interpret results causally. However, a series of strong assumptions have to be met (VanderWeele, 2016). We have to (1) control for exposure-outcome confounding effects, (2) control for mediator-outcome confounding effects, (3) control for exposure-mediator confounding effects, and (4) there should be no mediator-outcome confounder affected by the exposure. Assumptions (1) to (3) are easily achievable by introducing the right set of controls, aided by theory and previous research.

However, to meet (4) is more complex: *"the fourth assumption requires that nothing on the pathway from the exposure to the mediator itself also independently affects the outcome"* (VanderWeele, 2016, p.21). VanderWeele argues that if much time has passed between the exposure and the moment we measure the mediator, (4) is unlikely to be met. This is precisely the case in this dissertation. Several years pass between the exposure in early life until the moment the mediators and outcome are measured. Then, although Mediation Analyses interpret results causally, the effects found in *this* Mediation Analysis should be interpreted as associative rather than causally [8].

3.3 Econometric approach

A EWE is defined by a month that is above the 90^{th} or below the 10^{th} percentile in the monthly distribution of weather over the last 30 years [9]. This definition is applied both to temperature and rainfall. The first YL child of the Older Cohort in India was born in February 1993, and the last in August 1994. After constructing the weather distribution for each sentinel site from 1963 to 1992, each month's rainfall and temperature from June 1992 (when the first YL child was conceived) to August 1995 (when the last YL child reached age 1) are going to be designated with a 1 if it

[8]Lastly, the product method is still widely used, but other, more sophisticated Mediation Analysis approaches have surged over the past years. The most common is Structural Equation Modelling (SEM). This dissertation does not use SEM, as the necessary assumptions are stronger than with the product method (VanderWeele, 2012, 2016).

[9]Climatologists speak about climate after 30 years of weather (NASA, 2015).

was above the 90th or below the 10th percentiles, and 0 otherwise. For that reason, this dissertation uses the term Extreme Weather Month (hereafter EWM) rather than Extreme Weather Event. It is important to notice that this specification of weather shocks is exogenous to the income of the individuals.

Instead of grouping those months above the 90th and those below the 10th, each one would have its "own" variable. There are eight types of exposures: 4 variables for rainfall and 4 for temperature. Within each of those 4, 2 are dedicated for shocks during the gestation period, and the other 2 for shocks happening from birth until the child has reached age one (hereafter infancy). There is a final distinction between those EWM below the 10th and those EWM above the 90th percentiles. In general, this definition of EWE has been made to acknowledge the differences between rainfall and temperature shocks, pre- and post-birth. Figure 3.4 provides a clearer picture of the different EWM variables used.

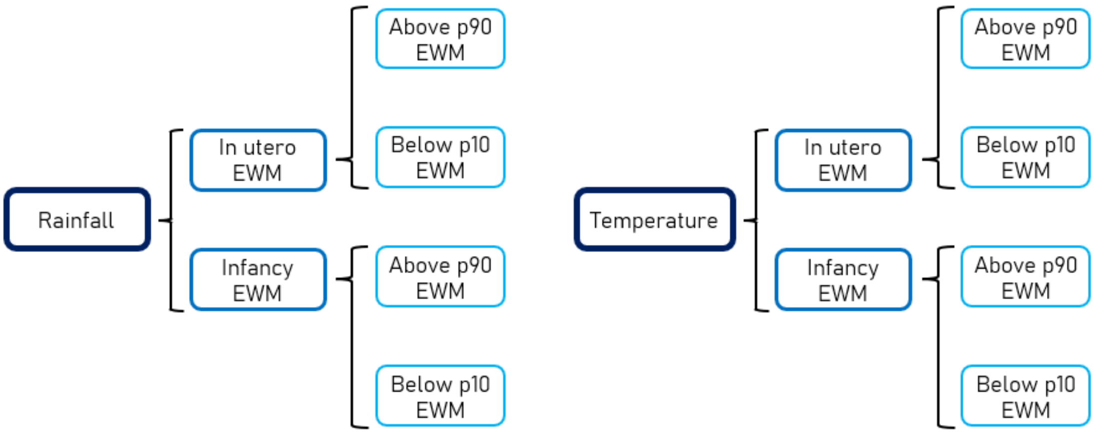

Figure 3.4: ***EWM variables used***

Source: self-elaboration

It is crucial to notice that each variable is continuous. Instead of measuring if a child suffered or not an EWM during gestation or the first year of life, this dissertation considers the *total* number of months that were extreme throughout this period. Thus, the in utero variables range from 0 to 9, and the infancy variables have values between 0 and 12. The alternative "dummy" definition is considered in a first robustness check.

Figures 3.5 and 3.6 present, respectively, the distribution of the number of rainfall and temperature EWMs. Most of the YL children have suffered between 0 and 2 extremely wet months, either during gestation or during infancy. However, exceptionally dry months are less frequent, with almost 300 children not exposed to this EWM.

In contrast, temperature EWMs (Figure 3.6) seem to portray a slightly more erratic histogram. Especially disturbing are the two variables below the 10th percentile ((b) and (d) graphs). There is an accumulation of YL children that suffered these exceptionally cold months (right-hand tail). These are entirely observations coming from cluster 4, located in a mountainous area in Coastal Andhra. Checking the UDel database, this area witnessed a continuous period of cold months from December 1992 to May 1995. We could manipulate the data and drop the YL children of this cluster. Instead, these children are included. The robustness check that

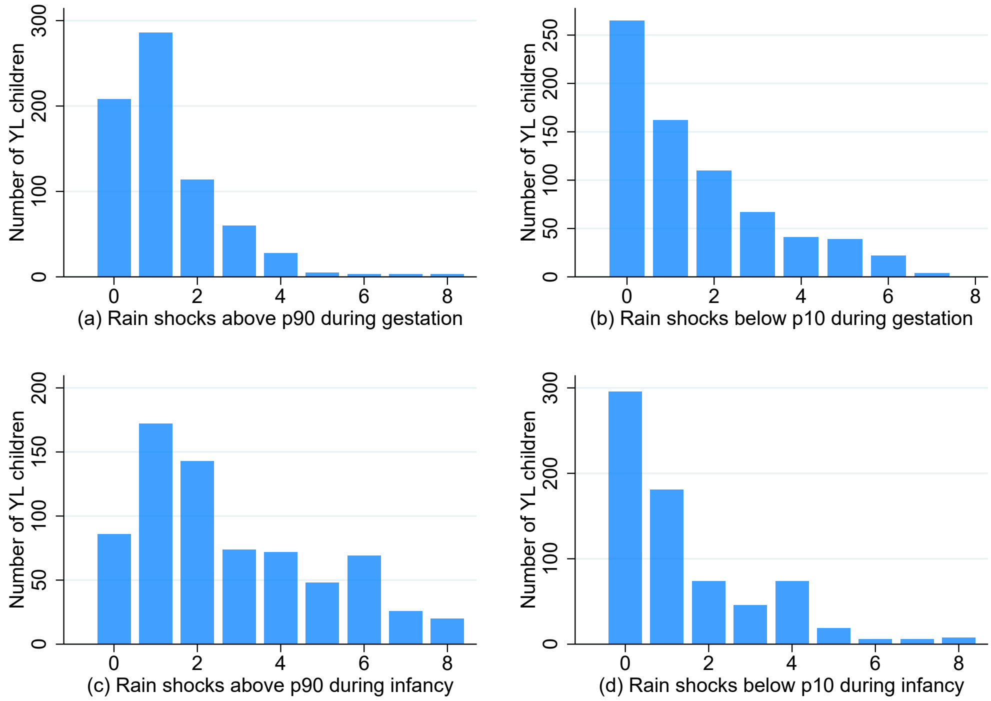

Figure 3.5: ***How many rainfall EWM suffered the YL children?***

Source: self-elaboration and Young Lives data (Boyden, 2018; Huttly and Jones, 2014)

applies a dummy definition to the EWM addresses the possibility that this cluster might be influencing the results.

Extreme percentiles in climate distributions have been widely used in papers that analyze the impact of EWM on humans in India (Jayachandran, 2006; Kaur, 2019; Shah and Steinberg, 2017). However, these articles consider the 80th and 20th as the cutoffs for designating shocks. They take a month over the 80th percentile of rainfall as a month with a positive rainfall shock. Conversely, a negative rainfall shock is defined as those months below the 20th percentile.

By selecting the 90th and the 10th percentiles, this dissertation takes a more restrictive view of the EWM. Using the 80/20 definition could include potential attenuation effects. For example, we would assign the same importance to months in the 96th and 82th percentiles, which is difficult to justify. In contrast, with the 90/10 definition, we ensure that most of the shocks within thresholds have a similar effect. Nevertheless, to test the validity of the 90/10 criteria, a couple of robustness checks repeat the main tables presented below for the 80/20 criteria and a more extreme 95/05 criteria.

A multiple set of mediators is considered rather than a single one. Again, the objective is to create a profile of how weather shock in early life affects children's income in early adulthood. For that profile to be complete, all the paths through which climate may affect labour outcomes have to be considered. Based on the literature review done, the mediators selected are:

- *Total Difficulties Score*: this index has been developed by the Young Lives team to measure the psychological abilities of the child. It is measured in

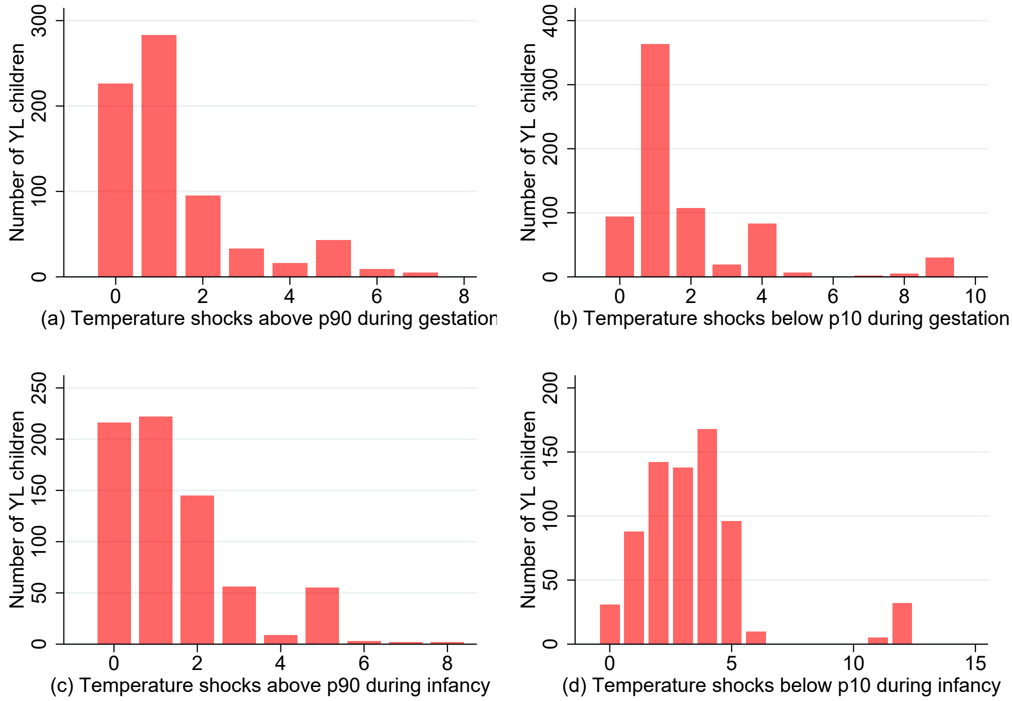

Figure 3.6: ***How many temperature EWM suffered the YL children?***

Source: self-elaboration and Young Lives data (Boyden, 2018; Huttly and Jones, 2014).

Round 1 (ages 7-8). It accounts for hyperactivity, conduct and peer problems and emotional distress. 2 equals normal behaviour, 1 equals borderline behaviour, and 0 equals abnormal behaviour. This variable accounts for the psychological health of the child.

- *Child height*: height of the child in Round 5 (age 22), to ensure that children have completed their physical development (Kuczmarski, 2002). This variable accounts for the physical health of the child. [10].

- *Test score:* an average mean between math and reading test scores, measured at Round 4 (age 19). This accounts for the cognitive ability of the child [11].

- *Highest educational level*: the highest level of education attained (primary or lower equal to 0, secondary to 1 and tertiary to 2) measured at Round 5.

- *Dropout and child labour*: based on the literature review about child labour and education, this variable equals 0 if the child dropped out of school *and* started child labour before age 13. It equals 2 if the child was in school *and* out of child labour until age 13. In the remaining intermediate category (equal to 1) are children that left school but did not start child labour and children that started child labour but continued in school (Emerson and Souza, 2011;

[10]Weight was also considered. However, height is a long-term accumulation of previous health experiences, like climatic shocks, whereas short-term factors might primarily determine weight.

[11]The high correlation (Pearson correlation coefficient around 0.69) between the maths and reading test is the reason to perform an arithmetic average.

Gunnarsson et al., 2006; Ilahi et al., 2000). It is measured at Round 2 (age 12). The inclusion of this mediator is one of the contributions of this dissertation.

The outcome of interest would be *lntotinc*, the logarithm of the total annual income received for all the activities performed [12], measured at Round 5, when the children are around 22 old [13].

Finally, there is a broad range of controls to meet the Mediation Analysis assumptions (1) to (3). These are demographic dummies by sex (1 if male), religion (1 if Hindu), language (1 if Telugu, the majoritarian in Andhra Pradesh), caste (1 if a discriminated caste), location (1 if urban sentinel site); and additional ones like the educational level of the caregiver of the child, age in months and if the household suffered food insecurity during Round 3 [14]. These standard controls are most likely not affected by the early life EWM variables considered here [15].

For the *Test score* regressions, the number of years in school is also added as a control. In the *lntotinc* regressions, three additional regressors are added: *wagempl* equals 1 if the YL child is receiving a performing wage employment, *regular* equals 1 if the YL child is working in regular employment (as opposed to seasonal employment, like agricultural ones), and *own* equals 1 if the YL child is performing the main activity for another member of the household or is self-employed.

This last control proves to be essential, as Figure 3.7 shows. The shaded area represents the kernel density of *lntotinc* from all the YL children. There is a significant accumulation of individuals who have a recorded income of 0, that is, YL children that perform some activity but are unpaid. These individuals represent a common thread in developing countries' labour markets: people that are unpaid while working (Msigwa and Kipesha, 2013).

However, if the shaded area is divided by the *own* variable, these unpaid YL children are mostly self-employed or employed by another member of the household ($own = 1$, the red line in Figure 3.7). This observation is consistent with the fact that a sizeable part of the active population in developing countries is self-employed and/or working in "family business", often the worst paid, *if they are paid* (Fields, 2011; Fox and Kaul, 2018; Msigwa and Kipesha, 2013).

This analysis takes the whole distribution instead of capping *lntotinc* and considering only those observations strictly above 0. First, the accumulation of individuals around 0 might be explained by the EWM variables used in this dissertation. In addition, the *own* variable controls for this bimodal shape. Nevertheless, a robustness check is made where all the individuals with 0 income are considered non-selected

[12] The few children that are paid by pieces produced are left out, as it is complex to construct a reliable measure of their annual income.

[13] It could be possible to construct the incomes of the children also in Rounds 3 and 4. However, these are not considered since incomes in these rounds are volatile: very few children work and receive income very sporadically throughout the year, which makes it challenging to compute a reliable measure of their annual income

[14] The food insecurity variable is not available for other rounds. Still, research has shown that households that suffered food insecurity once do not rebound and are likely to suffer other periods of food insecurity (Dornan et al., 2014). Thus, this control is added as a proxy for the whole level of food insecurity that a YL household has

[15] It may be argued that the same shocks that affected the YL child in early life might have conditioned the food situation of the household later. However, the Pearson correlation coefficient does not detect any correlation between the EWM variables and the food insecurity dummy. All coefficients are below 0.05.

in the Heckman correction model, explained below. [16].

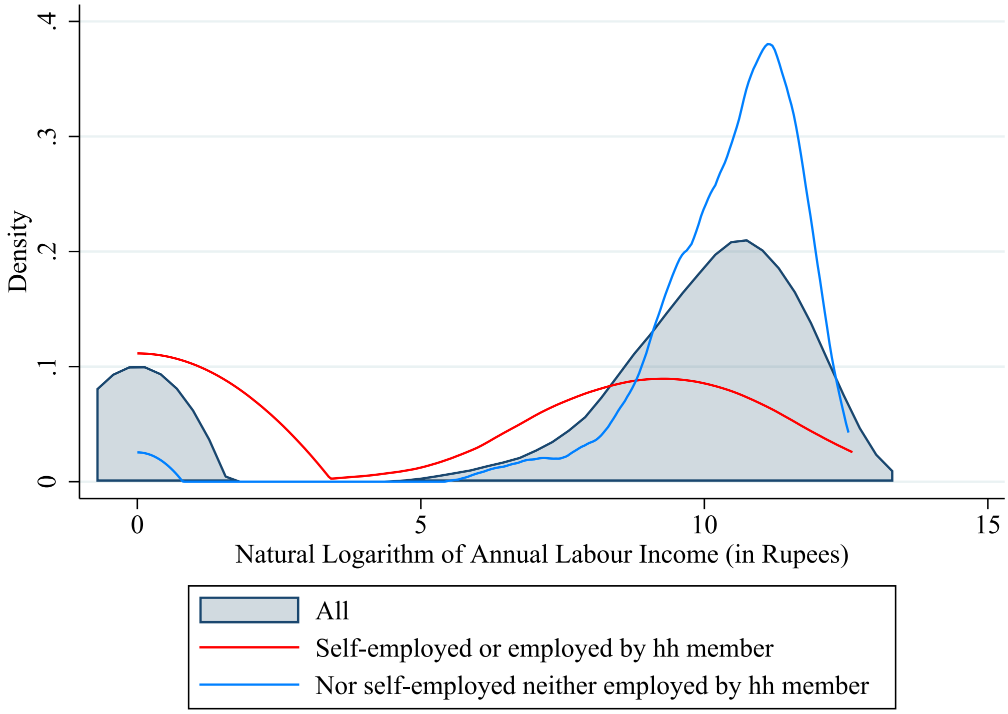

Figure 3.7: ***Kernel density of lntotinc***

Source: self-elaboration based on Young Lives data (Boyden, 2018; Huttly and Jones, 2014)

The conceptual depiction of the Mediation Analysis shown in Figure 3.3 is left as Figure 3.8 once all the variables mentioned above are included. In all the regressions performed here, wealth tertile fixed effects (computed for each round) are applied [17]. These are essential, as we want to account for the different climate impacts on the child depending on the wealth of his/her household. Also, clustered standard errors by sentinel sites are applied to account for omitted heterogeneity between YL sentinel sites. The additional regional fixed effects (recall Figure 3.1) are also applied.

Heckman correction

Before outlining the steps followed in the analysis chapter, a note has to be made regarding the outcome of interest *lntotinc*. This paper measures labour income at the beginning of the individual's professional life. The decision between working and continuing education happen during those years. Analyzing only those individuals working in each round would leave an incomplete picture, as the decision to keep education or be unemployed (or to neither continue education nor work, as happens with many girls) is also relevant. Because the individuals not working can be treated

[16]Furthermore, it may be argued that those active individuals with 0 recorded income might have other sources of income that help sustain themselves. Unfortunately, this cannot be addressed with the information coming from the YL study.

[17]The Young Lives study has developed a wealth index based on the household assets (Briones, 2017). Wealth tertiles are extracted from this index

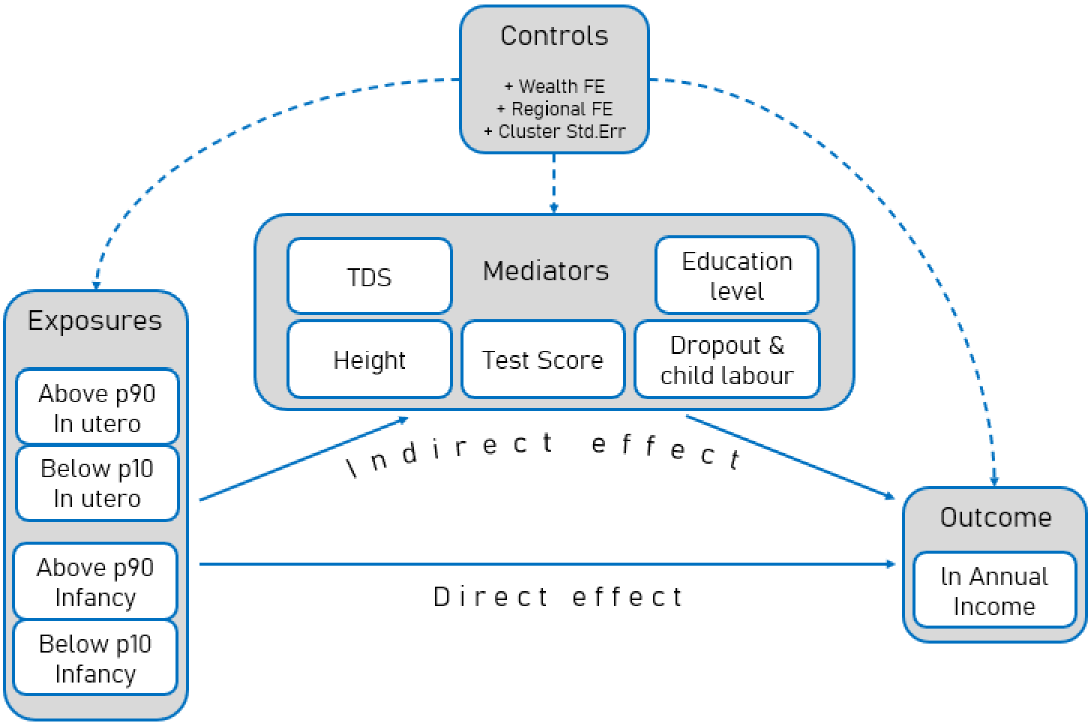

Figure 3.8: ***Mediation Analysis approach followed in this dissertation***

Source: self-elaboration based on Young Lives data (Boyden, 2018; Huttly and Jones, 2014)

as Missing Not At Random data, the Heckman sample selection model (Heckman, 1979) is a valid tool to tackle this problem.

Heckman's sample selection model addresses missing data in the dependent variable (income of the young adult), assuming that the missingness is not random. In this dissertation, a missing observation in income for a young adult comes from the fact that he or she has decided not to work, and this decision is not random, and we should correct our base estimates by acknowledging that (Enders, 2010).

Essentially, Heckman is a two-step model, although the results presented in Chapter 4 are estimated via Maximum Likelihood. First, the first equation represents the main model,

$$Y'_{1i} = X_i\beta + u_i \tag{3.4}$$

... and the second equation represents the selection model,

$$Y'_{2i} = Z_i\lambda + v_i \tag{3.5}$$

If the latent variable Y'_{2i} is above a giving threshold, $Y_{2i} = 1$. Then Y_{1i} will be observed. In our case, if a YL child has a recorded activity, this observation is considered as observed (or *selected* in Heckman's jargon). Those non-observed observations are individuals that do not have a recorded activity. Then the Heckman model corrects for the fact that both equation's errors are correlated (since it is a process of Missing Not at Random). The correction is left as:

$$Y_{1i} = X_i\beta + p\lambda + e_i \tag{3.6}$$

Where p is the correlation between the two errors u_i and v_i (Wolfolds and Siegel, 2019).

Nevertheless, the Heckman model should be used more like a sensitivity analysis than any study's central part. This is because this model is highly sensitive to the specific functional form of the two equations. In addition, there is multicollinearity between the two equations. In practice, some instrumental variables are used only for the selection equation but not for the main equation to address this problem (Wolfolds and Siegel, 2019; Enders, 2010).

Acknowledging this, for the regressions that use the Heckman model, two instrumental variables will be used: *birth* equals 1 if the YL child has a child of his own, and *enrol* equals 1 if the individual is enrolled in formal education in the present round [18]. These variables are most likely to influence the decision of working or not, but not the income earned [19] [20].

All the variables used in this dissertation have been described. Their summary statistics are presented next. The total number of individuals is N=710. These are the YL children whose mothers already lived in the YL village at the moment of conception. In that way, we can assure that the YL children in the subsample were exposed to the EWM considered here [21]. This subsample seems relatively well-educated and with low school dropout levels. Of those 710 individuals, 427 have a recorded activity, with 35% of them being in regular employment and 40% self-employed or employed by another household member. Additionally, 23% of the subsample is still in education, and another 23% has already a child.

Step 0: EWM effect on *lntotinc* with no mediators

This methodology chapter ends with a description of the step by step procedure that this dissertation applies to perform the Mediation Analysis. In a preliminary step, the EWM variables will be used as explanatory variables of the children's income without including the mediators as additional explanatory variables. In other words, the Total Effect of the EWM variables on income is measured. The regressions, performed separately for rainfall and temperature EWMs, look as follows:

$$lntotinc_i = \beta_0 + \beta_k^{'} EWM_{ik} + \beta^{'} C_i + e_i \tag{3.7}$$

[18] *marrcohab*, a variable that equals 1 if the YL child is married was also considered. However, given the high correlation between *marrcohab* and *birth*, the first was finally dropped from the analysis.

[19] Obviously, having a child or being enrolled in formal education might have an impact on income. For example, students might accept lower wages while they are enrolled. However, both variables *birth* and *enrol* were not significant if introduced in the main equation.

[20] Should the mediators be considered as controls in the selection equation? One of the main problems of using the Heckman model is the extreme multicollinearity that arises due to having the same sets of variables in the selection and main equation. Again, for that reason, *birth* and *enrol* are added as instruments. However, adding another set of variables (i.e., the mediators) in both equations would increase the multicollinearity problem. Therefore, the mediators are not included in the selection. The results presented below do not change substantially if we include the mediators in the selection equation or not. If any, the significance of the EWM variables increases slightly.

[21] This represents an extraordinary benefit of the YL study, as other articles cannot discern the location of conception and, thus, their analysis of climatic shock might present endogeneity due to measuring errors (Wilde et al., 2017).

Table 3.1: *Summary statistics of all the variables used for the Mediation Analysis*

Variable	Additional information	Obs.	Mean	Std. Dev.	Min	Max	At age
Controls							
Sex	1 if male	710	0,49	0,50	0	1	22
Religion	1 if Hinduism	710	0,89	0,32	0	1	22
Caste	1 if non-discriminated caste	710	0,20	0,40	0	1	22
Language	1 if Telugu	710	0,86	0,35	0	1	22
Type of location	1 if urban	710	0,29	0,46	0	1	22
Food insecurity	1 if suffered during round 3	710	0,07	0,25	0	1	15
Wealth Index	Poorest tertile	310	0,54				22
	Middle Tertile	319	0,66				
	Richest Tertile	295	0,76				
Region	Coastal Andhra	257	0.36				22
	Rayalaseema	198	0.28				
	Telangana	255	0.36				
Mediators							
Height	In cm	706	159,43	9,59	106,5	184,50	22
Mean of test score	In percentage	705	53,67	18,92	6,25	96,67	19
TDS	0 if abnormal behaviour	137	0.19				8
	1 if borderline behaviour	129	0.18				
	2 if normal behaviour	443	0.62				
Highest educational level	0 if primary or lower	38	0.05				22
	1 if secondary	318	0.45				
	2 if tertiary	354	0.50				
Dropout & child labour bef. 13 y/o	0 if both	24	0.03				12
	1 if one of the two options	151	0.21				
	2 if none	535	0.75				
Outcome							
Ln Total Income	In Rupees	427	7,96	4,37	0	12,61	22
. . . and additional controls							
Regular employment	1 if regular employment	427	0,35	0,48	0	1	22
Wage employment	1 if wage employment	427	0,70	0,46	0	1	22
Own employment	1 if self-employed or employed by other member of the hh	427	0,40	0,49	0	1	22
Heckman instruments							
Enrollment	1 if enrolled in formal education	710	0,23	0,42	0	1	22
Birth	1 if YL child has a child	710	0,23	0,42	0	1	22

Source: self-elaboration based on Young Lives data (Boyden, 2018; Huttly and Jones, 2014).
Note: for the dummy variables, the *mean* column represents the % of individuals in each category.

Where $\beta_k^{'}$ is a vector with the k coefficients of the k EWM variables, being $k = 4$, as explained in Figure 3.4. The Heckman selection equation is left as follows:

$$selected_i = \phi_0 + \phi_1 birth + \phi_2 enrol + \phi^{'} C_i + e_i \tag{3.8}$$

Where $selected_i$ is a dummy variable that equals 1 if an individual i has performed a work activity and 0 otherwise. The selected YL children can have 0 income (recall Figure 3.7), as this reflects the commented characteristic of developing labour markets: unpaid workers, many of them in a family business or self-employed.

Step 1: EWM effect on mediators

The first step of the proper Mediation Analysis is to observe how climate shocks in early life affect the outcomes described above. The regression for each mediator m is left as follows:

$$M_i{}^m = \beta_0 + \beta_k^{'} EWM_{ik} + \beta^{'} C_i + e_i \tag{3.9}$$

It is important to acknowledge that every regression is a standard OLS. This is not an issue for the *height* and *meantest* regressions. However, TDS, *hghlevel* and $bothbef13$ are categorical variables. Applying a *linear* estimation such as OLS to variables that are not linear has its inconveniences. Mainly, the results cannot be interpreted as easily as the odds ratios in an ordered probit specification. However, OLS has been chosen since this dissertation uses the product method of the Mediation Analysis. If probit would be chosen, to obtain the Indirect Effect, we would multiply coefficients coming from probits and OLS, which does not produce any interpretable results [22] [23].

Step 2: EWM effect on *lntotinc* with mediators

Essentially, this step replicates Step 0 but adding the mediators as additional controls. The equation remains as:

$$lntotinc_i = \theta_0 + \theta_k^{'} EWM_{ik} + \theta_m^{'} M_i + \theta^{'} C_i + e_i \tag{3.10}$$

Where $\theta_k^{'}$ is a vector of the k coefficients of the k EWM variables. $\theta_m^{'}$ is a vector of the m coefficients of the m mediators. Being $k = 4$ and $m = 6$. as explained in Figure 3.4. The Heckman selection equation is left as:

$$selected_i = \phi_0 + \phi_1 birth + \phi_2 enrol + \phi^{'} C_i + e_i \tag{3.11}$$

Step 3: Computation of the Direct and Indirect Effects

Lastly, the final step is the partition of the Total Effect between the Direct and Indirect Effects:

$$TE'_k = DE'_k + IE'_{km} = \theta_k^{'} + \beta_k^{'} \theta_m^{'} + e_i \tag{3.12}$$

There is a vector of k Total Effects since we have k EWM variables. These are split between the k Direct Effects ($\theta_k^{'}$ from step 2) and the km Indirect Effects ($\beta_k^{'}$ from step 1 and $\theta_m^{'}$ from step 2).

EWM differential effects

In an additional analysis, this dissertation assumes that shocks can have differential effects depending on gender, trimester of gestation and season of the year, as the literature shows that climate can affect differently depending on these characteristics (Rosales-Rueda, 2018; Saulnier and Brolin, 2015; Hyland and Russ, 2019; Maccini and Yang, 2009). This is further explained at the end of the next chapter.

[22] Although the use of OLS is forced, using the ordered probit estimation does not change the sign of the results. However, there is a slight decrease in the significance levels because the probit fits the data better than the OLS. Therefore, these "forced OLS" are not that problematic: if any, we could have false negatives (Error Type II), but false positives (Error Type I) are less likely.

[23] VanderWeele and Vansteelandt (2014) explain a Mediation Analysis using multiple binary mediators, but not categorical variables.

4. Analysis

4.1 Step 0: EWM effect on income with no mediators

In this first step, the Total Effect of climate shocks in early life on initial labour incomes is observed. As a reminder, this preliminary step is not a part of the Mediation Analysis. It gives introductory insights into the relationship between EWM and income. Table 4.1 reports only coefficients for the four EWM variables.

In Panel A, the EWM specification used here leaves no significant effect of rainfall shocks on labour income. However, the signs of the coefficients are rather interesting. In utero rainfall shocks impacts negatively income, regardless if we introduce fixed effects by region or not. Across the four EWM variables, the ones signalling months above the 90$^{\text{th}}$ percentile seems to have a higher impact in absolute terms.

In Panel B, we observe the opposite direction of signs: temperature shocks positively impact income if they happen during gestation and a negative impact if they happen during infancy. In addition, it is now the months below the 10$^{\text{th}}$ percentile the ones that display a more potent effect, with some coefficients being significantly different from zero. An additional extremely cold month during gestation reduces the child's income by 24%, all things equal. Both panels suggest that rainfall and temperature EWMs have a different impact on the fetus and the child after birth.

A final note on Table 4.1 is that the Heckman correction columns do not seem to change much of the base coefficients. This implies that there is not much selection effect in our sample: instead of having Missing Not At Random data, it seems that we are closer to a Missing At Random setup. In line with this observation, the correlation of the errors of the main and selection equations (p in equation 3.6) is close to being not significantly different from zero (Enders, 2010).

In these regressions, the two instruments used, *enrol* and *birth*, enter significantly (above 1%) and negatively. Being enrolled at school reduces the probability of having an income, and also does having a child. This second result is puzzling, as having a child should push the parent to look for work. However, of all the YL individuals who have children (N=226) in Round 5, 205 are women. In India, women can marry at the age of 18, whereas men since age 21 (GOI, 2012). This age gap implies that some women in our sample had been already married for at least four years. Meanwhile, male individuals had not had time to bear their children at age 22. In short, the negative effect of *birth* is explained because females tend to stay at home looking for their children. After some years have passed, more males will start to bear children, and hence the negative sign should turn close to zero since having a child is no longer a predictor of observing a wage or not.

Table 4.1: *Early life weather shocks effect on labour income*

EWM variable		Ln income ...at 22 y/o: Basic	Ln income ...at 22 y/o: Heckman corrected	Ln income ...at 22 y/o: Basic	Ln income ...at 22 y/o: Heckman corrected
		Panel A: Rainfall shocks			
In utero	Above p90	-0.075	-0.076	-0.088	-0.090
		(0.102)	(0.101)	(0.125)	(0.124)
	Below p10	-0.019	-0.013	-0.029	-0.024
		(0.099)	(0.095)	(0.091)	(0.088)
Infancy	Above p90	0.056	0.060	0.051	0.054
		(0.078)	(0.078)	(0.083)	(0.082)
	Below p10	0.028	0.031	-0.003	-0.004
		(0.114)	(0.112)	(0.133)	(0.129)
	R2	*0.622*		*0.622*	
	N	*427*	*710*	*427*	*710*
	Wealth FE	*YES*	*YES*	*YES*	*YES*
	Regional FE	*NO*	*NO*	*YES*	*YES*
		Panel B: Temperature shocks			
In utero	Above p90	-0.039	-0.047	0.017	0.014
		(0.109)	(0.108)	(0.122)	(0.120)
	Below p10	0.145	0.141	0.237**	0.240**
		(0.105)	(0.104)	(0.112)	(0.111)
Infancy	Above p90	-0.060	-0.056	-0.049	-0.041
		(0.104)	(0.103)	(0.101)	(0.099)
	Below p10	-0.104	-0.104	-0.137*	-0.139*
		(0.084)	(0.083)	(0.076)	(0.075)
	R2	*0.624*		*0.625*	
	N	*427*	*710*	*427*	*710*
	Wealth FE	*YES*	*YES*	*YES*	*YES*
	Regional FE	*NO*	*NO*	*YES*	*YES*

(Dependant variable: Ln income)

Source: self-elaboration based on Young Lives data (Boyden, 2018; Huttly and Jones, 2014).
Note: Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Table reads as follows: a rainfall shock in utero above p90 reduces the income by approximately 7.5%, not including Regional FE. If we apply the Heckman correction, this effect changes to a reduction of 7.6%

4.2 Step 1: EWM effect on mediators

Step 1.A: Rainfall EWM effect on mediators

In this first step of the Mediation Analysis, we will observe how the EWM variables affected different intermediate outcomes of the child. Table 4.2 reports the results for the rainfall shocks. This set of coefficients is the β_k' of equation 3.9. For simplicity, only the most relevant results of the Regional FE panel will be commented on, as there are only small differences between the two panels, at least in terms of the sign of the coefficients.

There are no significant effects on the children's psychological health or their cognitive status. However, to have suffered months with too little rainfall during pregnancy *increases* the height significantly. Some authors observe a rebound in

Table 4.2: Early life rainfall shocks effect on mediators

EWM variable		Total difficulties score ...at 8 y/o	Child height ...at 22 y/o	Child test score ...at 19 y/o	Highest educational level ...at 22 y/o	Dropout & child labour bef. 13 y/o ...at 13 y/o
		Dependant variables				
In utero	Above p90	0.025	-0.244	0.564	0.002	0.039*
		(0.042)	(0.185)	(0.591)	(0.015)	(0.019)
	Below p10	-0.041	0.257*	-1.015	-0.029*	-0.049***
		(0.025)	(0.134)	(0.599)	(0.016)	(0.013)
Infancy	Above p90	0.002	-0.028	-0.422	-0.034***	-0.044***
		(0.021)	(0.102)	(0.373)	(0.007)	(0.014)
	Below p10	-0.054*	-0.304***	-0.784	-0.024	-0.001
		(0.031)	(0.104)	(0.587)	(0.016)	(0.027)
	R2	*0.093*	*0.613*	*0.289*	*0.143*	*0.112*
	N	*709*	706	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*NO*	*NO*	*NO*	*NO*	*NO*
In utero	Above p90	0.029	-0.176	0.152	0.014	0.009
		(0.039)	(0.194)	(0.618)	(0.018)	(0.026)
	Below p10	-0.025	0.268**	-0.689	-0.025	-0.051***
		(0.025)	(0.124)	(0.472)	(0.016)	(0.016)
Infancy	Above p90	0.016	-0.026	-0.087	-0.031***	-0.040***
		(0.023)	(0.100)	(0.256)	(0.005)	(0.012)
	Below p10	-0.014	-0.207	-0.453	-0.001	-0.027
		(0.037)	(0.125)	(0.662)	(0.021)	(0.028)
	R2	*0.109*	*0.613*	*0.307*	*0.149*	*0.151*
	N	*709*	706	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*

Source: self-elaboration based on Young Lives data (Boyden, 2018; Huttly and Jones, 2014).
Note: Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.. The total number of observations is 710. The columns with less observations portray differences between rounds. For example, the TDS column, one child did not get a psychological evaluation at age 8, but his income was computed at age 22.

height for the children that have suffered extreme monsoons (Tiwari et al., 2017). However, one thing is a rebound to a normal height-for-age, and another is a rebound that surpasses that.

Therefore, these results introduce a possibility commented on in the theoretical review: the selection effect. Weak fetuses and children that suffered shocks might (1) have deceased before were measured by the YL study or (2) during the YL itself. Only the "strongest" may have lived. Regarding (1), the only thing the YL study allows is to observe how many children the family of each YL child lost before the YL child was born. In this sample of 710 children, the YL households lost between 0 and 5 children. The YL children that lived in a household with 0, 1, 2 and 3 deaths had a mean height of 159, 160, 159 and 152 cm, respectively, in Round 5. Households with 4 and 5 deaths should not be considered as there are only 5 with this amount of lost children. In short, shorter YL children live in households that lost more children. This points in the direction that the lost children might have been shorter in stature, as they lived in "shorter" households, meaning households with poorer nutritional status. The YL families that had food insecurity during

Round 3 had lost more children *before Round 1*. Once food insecurity appears, the household does not rebound and continues to have periods of recurrent hunger (Dornan et al., 2014), which translates into higher mortality among children.

However, the exact moment of these deaths is unknown. It may have been the case that the household changed over time in terms of parents' experience, household income, migration, etc. Furthermore, we are interested in both the selection effects of the lost siblings of the YL children *and* the selection effect of YL children. For (2) (i.e., the weakest YL children might have died), we observe that 18 YL children measured in Round 1 did not make it to Round 5. If we compare the heights at age 8 of the YL children that lost their lives with those that did not, we see that the deceased ones are more than 3 cm *shorter* than the living ones. This partially confirms a slight selection effect before and after Round 1 of the YL study.

However, are EWMs a possible cause of this selection effect? On average, the deceased children suffered 8.8 rainfall EWM, while the rest had only 7.14. However, for the significant *below p10* EWM variable, the difference is severely reduced (1.61 and 1.60, respectively). This selection effect is further studied later in this chapter.

The educational and child labour mediators are also affected by rainfall shocks in Table 4.2. Especially if too little rainfall was received during gestation or too much rainfall was received during infancy. Children who lived these two types of EWM more frequently have more chances to drop school and do child labour by age 13 and, consequently, have lower educational attainment by age 22. This is a shocking result, even more considering that the cognitive status of the children does not seem to be affected by rainfall EWM. One would not expect early life EWM several years ago make the household more prone to withdraw the child out of school.

One plausible explanation for this odd result maybe the location of the household. In this sample, YL children living in rural households during their early life suffered more EWMs than the YL children in urban areas [1]. Also, for this sample, urban children are more likely to stay at school and not perform child labour before age 13 [2].

Then, the adverse effects found for this mediator may come from the fact that rural areas in Andhra Pradesh seem to be more exposed to rainfall shocks. If this pattern has continued since the child's early life, these negative shocks will have continued to occur, affecting, for example, the household agricultural output. Research has shown that this, in turn, impacts the household education and child labour decisions (Basu and Van, 1998; Beegle et al., 2006). Nevertheless, to my knowledge, no other article addresses how early life climate shocks affect child labour. Therefore, the novel evidence presented here represents an exciting new research line.

Step 1.B: Temperature EWM effect on mediators

Table 4.3 reports the results for temperature EWM. In this set of regressions, the differences between the panels applying or not the Regional FE are more explicit. The significance of the coefficients mostly diminishes when the Regional FE are introduced. This points to the fact that regional temperature differences might be behind most of the effects. It is interesting to see in Table 4.2 that regional rainfall

[1] Rural children suffered 1.59 dry EWMs in utero, while urban ones only 1.45. Also, rural children suffered 2.83 wet EWMs during infancy, while urban ones suffered only 2.59.

[2] Rural children mean value for the dropout and child labour mediator: 1.68. For urban children, this increases up to 1.80.

differences were not that crucial.

Table 4.3: Early life temperature shocks effect on mediator

EWM variable		Total difficulties score ...at 8 y/o	Child height ...at 22 y/o	Child test score ...at 19 y/o	Highest educational level ...at 22 y/o	Dropout & child labour bef. 13 y/o ...at 13 y/o
		Dependant variables				
In utero	Above p90	0.065***	0.115	1.074*	0.023	-0.027
		(0.018)	(0.225)	(0.566)	(0.014)	(0.030)
	Below p10	0.080***	-0.060	1.751***	0.031*	0.050**
		(0.021)	(0.151)	(0.423)	(0.016)	(0.023)
Infancy	Above p90	0.026	-0.062	-1.249**	-0.001	-0.026
		(0.019)	(0.293)	(0.475)	(0.019)	(0.018)
	Below p10	-0.021	0.060	-1.313***	0.004	-0.026*
		(0.018)	(0.151)	(0.330)	(0.010)	(0.013)
	R2	*0.097*	*0.609*	*0.291*	*0.136*	*0.106*
	N	*709*	*706*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*NO*	*NO*	*NO*	*NO*	*NO*
In utero	Above p90	0.038**	-0.013	0.070	0.009	-0.034
		(0.014)	(0.262)	(0.566)	(0.014)	(0.030)
	Below p10	0.044	-0.119	0.095	0.025	0.012
		(0.028)	(0.204)	(0.511)	(0.017)	(0.027)
Infancy	Above p90	0.018	-0.107	-1.576***	-0.006	-0.029
		(0.017)	(0.274)	(0.407)	(0.018)	(0.018)
	Below p10	-0.013	0.016	-0.788**	-0.002	-0.002
		(0.017)	(0.164)	(0.363)	(0.009)	(0.012)
	R2	*0.103*	*0.611*	*0.313*	*0.143*	*0.143*
	N	*709*	706	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*

Source: self-elaboration based on Young Lives data (Boyden, 2018; Huttly and Jones, 2014).
Note: Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Again, only the results of the Regional FE panel are commented on. The most striking result is that experiencing very high temperatures in early life has a significant *positive* effect on the psychological health of the child. Could a psychological selection effect exist? A possible "mental resilience mechanism" (Masten, 2001) (i.e., tougher times might create mentally tougher individuals) does not have much sense since the shocks happened during gestation. Nevertheless, as these are shocks that happened during gestation, this puzzling result is further studied in Table A.4, where EWM variables are desegregated by trimester of gestation.

Contrary to what happened in the previous rainfall table, there is no impact on height. If there is a selection effect, this might come exclusively through rainfall EWM.

Where these extreme temperatures affect the most is at the cognitive level. One more month with exceptionally warm temperatures during infancy reduces the mean test score by 1.5 percentage points, ceteris paribus. However, this cognitive handicap is not transferred into worse educational attainment. Finally, there is no effect on the dropout mediator.

In short, for our sample considered here, it seems like rainfall and temperature

EWM impact the set of mediators chosen differently. Rainfall shocks affect heights, educational level and early education and child labour decisions. On the other hand, temperature shocks have more substantial effects on the psychological and, primarily, the cognitive level of YL children.

Aside from showing important results, Tables 4.1, 4.2 and 4.3 underscore two things. Firstly, from Table 4.1, the Heckman correction does not alter much the size or significance of the coefficients. Since it has more observations and lower standard errors by definition, only the Heckman correction will be presented in the following regressions.

Secondly, from Tables 4.2 and 4.3, we can see that including Regional Fixed Effects is decisive in obtaining more refined results, especially for temperature EWM. For this motive, Regional FE will be applied by default in the following regressions.

4.3 Step 2: EWM effect on income with mediators

This second step adds the mediators as controls that may explain how early life weather shocks affect income. The results presented in Tables 4.4 and 4.5 are the $\theta_k^{'}$ and $\theta_m^{'}$ of equation 3.10. $\theta_k^{'}$ are the coefficients of the EWM variables, and the $\theta_m^{'}$ are the coefficients of the mediators.

Step 2.A: Rainfall EWM effect on income with mediators

Table 4.4 portrays the effect of the rainfall EWM variables on annual income, including the mediators as controls. Columns 1 to 5 introduce one mediator at a time. Column 6 considers the complete set of mediators together. As we saw in Step 0 (Table 4.1), rainfall shocks do not seem to have a significant direct impact on the income of the YL children. The inclusion of the mediators does not change that. Across the different columns, suffering extremely wet months in utero have the highest impact. One more month of these characteristics reduces income (non-significantly) by 9.2%, all things equal. The rest of the EWM variables have positive and much smaller coefficients.

To analyse the impact of mediators, column 6 serves as the main reference. Mediation Analyses with multiple mediators, as is the case in this dissertation, have to consider the possibility that the mediators affect one another (VanderWeele and Vansteelandt, 2014). Indeed, cognitive results, educational level and the dropout measure are most likely influencing each other. The mean test score and the educational level have a Pearson correlation coefficient of 0.58, and the dropout measure and the educational level of 0.32. The rest of the correlations between mediators are below 0.3. Therefore, column 6 stands as the best estimation since it acknowledges the correlation between mediators, and we can observe coefficients "net" of other mediators.

The Total Difficulties Score is non-significant in column 1. Having a more stable psychological behaviour (higher TDS) is weakly correlated with having more income, which is expected (Wright and Cropanzano, 2004). One could argue that income is the one influencing psychological well-being, not the other way around. There is extensive literature from Psychology and Economics that has proven this link (see Syrén et al. (2020) for a recent review). However, TDS is measured when

Table 4.4: Early life rainfall shocks effect on labour income with mediators

		Dependant variable					
		Ln income: Heckman corrected ...at 22 y/o					
		(1)	(2)	(3)	(4)	(5)	(6)
EWM variable							
In utero	Above p90	-0.093	-0.090	-0.093	-0.084	-0.092	-0.092
		(0.128)	(0.124)	(0.128)	(0.123)	(0.123)	(0.123)
	Below p10	-0.023	-0.009	-0.023	-0.020	-0.012	0.019
		(0.087)	(0.090)	(0.087)	(0.086)	(0.086)	(0.086)
Infancy	Above p90	0.053	0.052	0.048	0.030	0.063	0.044
		(0.081)	(0.082)	(0.084)	(0.081)	(0.078)	(0.075)
	Below p10	-0.003	-0.011	-0.009	-0.009	0.007	0.006
		(0.131)	(0.132)	(0.131)	(0.131)	(0.119)	(0.121)
Mediators							
	TDS	0.040					0.067
		(0.142)					(0.126)
	Height		-0.028				-0.027
			(0.023)				(0.023)
	Test Score			-0.014*			-0.003
				(0.008)			(0.009)
	Highest edu. level				-0.826***		-0.880***
					(0.272)		(0.287)
	Dropout & child labour bef. 13 y/o					0.277	0.527**
						(0.241)	(0.232)
	N	710	710	710	710	710	710
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Source: self-elaboration based on Young Lives data (Boyden, 2018; Huttly and Jones, 2014).
Note: Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

the individual is at age 8 and income at 22. Therefore, this reversed direction of causality is ruled out, as future income cannot influence present well-being [3].

In column 2, surprisingly, taller individuals have less income, which goes against the evidence that more height predicts an increased career success (Judge and Cable, 2004). Nevertheless, the coefficient is non-significant in both columns 2 and 6.

Moving to the mean test score, this mediator harms income (column 3), although the significance is suppressed after the other mediators are introduced in column 6. This points to the fact that test scores' effect on income is probably mainly driven by the level of educational attainment.

The most interesting result of Table 4.4 is that educational attainment appears to have a strongly significant *negative* effect on income in both columns 4 and 6. How could it be that the more education the individual has, the lower his income? One must consider the sample with which this dissertation works to answer that question. Young adults around age 22 are at the beginning of their professional careers, especially those who have tertiary education. In India, secondary school ends at age 18, and bachelor's degrees typically last three years (MHRD, 2014).

[3] Another possibility is that parental income influences children's psychological well-being, which in turn alters the children's income in the future (Johnston et al., 2013). Studying this psychological-poverty trap is out of the scope of this dissertation.

Therefore, assuming that individuals have not repeated courses, most YL children who pursued higher studies started their working life around one year before Round 5.

Although returns to education in developing countries are higher than in developed ones (O'Higgins, 2003; Psacharopoulos and Patrinos, 2002), these do not manifest immediately. Unemployment rates of highly educated individuals are high in developing countries (Van der Geest, 2010; Fares et al., 2006). In our YL sample, there is an unemployment rate of 39% among those with tertiary education and not enrolled [4]. On the other hand, the unemployment rate of individuals with finished secondary education is 29%.

Furthermore, in developing countries, many of these young educated individuals are often unpaid or low paid (Msigwa and Kipesha, 2013). This is precisely the reality that is capturing the extremely negative coefficient of the educational level on income: young, well-educated but *highly inexperienced* individuals that are low paid at the beginning. The YL children with the higher mean income are those with a finished secondary education.

This "late start penalty" may also explain the significant effect of mean test scores on income. Those with higher scores are more likely to be at higher educational levels. Therefore, if the educational level mediator is introduced in column 6, the coefficient of test scores ceases to be significant.

Finally, the dropout measure also displays a significant effect on income. Staying in school and not having worked before the age of thirteen has beneficial effects on later earnings outcomes. This is entirely in line with the literature that underscores the importance of neither dropping out of school nor performing child labour at a very early age (Emerson and Souza, 2011; Ilahi et al., 2000; Gunnarsson et al., 2006). Additionally, at the same time that educational attainment wipes out the importance of the test scores, now it *enhances* the effect of the dropout mediator. This probably signals that, between those individuals with the same educational attainment, the ones who did child labour very early are in worse condition, probably in worse occupations.

Step 2.B: Temperature EWM effect on income with mediators

Table 4.5 shows the results for the temperature EWM. Again, the coefficients of the EWM variables and the mediators are represented by θ'_k and θ'_m respectively, coming from equation 3.10. First of all, the mediators' coefficients are fairly similar to those in Table 4.4. This is expected, as the inclusion of rainfall EWM or temperature EWM variables should not alter the impact that third variables (the mediators) have on income.

As Table 4.1 reports, and in sharp contrast with the previous Table 4.4, temperature EWM variables do have an effect on income. More specifically, suffering exceptionally cold EWM during gestation increases the income of the YL children, but the same months during the first year decrease it. The rationale for this change pre- and post-birth is analysed at the end of this chapter.

In anticipation of the next step 3, one can foresee that the Indirect Effect of equation 3.3 for temperature EWM is going to be small. The differences between the coefficients of the last column in Panel B of Table 4.1 and those in column 6 in

[4] Of the total 203 YL children with finished tertiary education, 79 do not have any recorded activity.

Table 4.5: Early life temperature shocks effect on labour income with mediators

		Dependant variable					
		Ln income: Heckman corrected ...at 22 y/o					
		(1)	(2)	(3)	(4)	(5)	(6)
EWM variable							
In utero	Above p90	0.014	0.017	0.015	0.049	0.017	0.059
		(0.122)	(0.118)	(0.122)	(0.113)	(0.123)	(0.116)
	Below p10	0.238**	0.235**	0.223**	0.237**	0.232**	0.212*
		(0.113)	(0.111)	(0.111)	(0.107)	(0.111)	(0.108)
Infancy	Above p90	-0.041	-0.043	-0.064	-0.071	-0.037	-0.070
		(0.099)	(0.099)	(0.099)	(0.096)	(0.097)	(0.091)
	Below p10	-0.139*	-0.137*	-0.139*	-0.143*	-0.140*	-0.141*
		(0.075)	(0.076)	(0.078)	(0.077)	(0.074)	(0.077)
Mediators							
	TDS	0.020					0.034
		(0.157)					(0.135)
	Height		-0.027				-0.025
			(0.022)				(0.022)
	Test Score			-0.014*			-0.002
				(0.008)			(0.009)
	Highest edu. level				-0.835***		-0.894***
					(0.272)		(0.287)
	Dropout & child labour bef. 13 y/o					0.204	0.459*
						(0.278)	(0.258)
	N	710	710	710	710	710	710
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Source: self-elaboration based on Young Lives data (Boyden, 2018; Huttly and Jones, 2014).
Note: Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table 4.5 are minimal. This means that the inclusion of mediators has not changed the impact of the temperature EWM variables on income. This is further discussed below.

4.4 Step 3: Computation of Direct and Indirect Effects.

This subsection finalises the steps followed in the Mediation Analysis. Table 4.6 shows the Direct and Indirect Effects of the different EWM variables on the total annual income of the YL children. As a reminder, the Direct Effect (DE) columns display the coefficients of the θ'_k of equation 3.12. These were previously shown in columns 6 of Tables 4.4 and 4.5. The Indirect Effect (IE) coefficients perform the product of the coefficients β'_k and θ'_m, also from 3.12. Again, the β'_k were previously shown in Tables 4.2 and 4.3, and the θ'_m in columns 6 of Tables 4.4 and 4.5 [5].

This Table 4.6 repeats in the DE rows some results already commented. In Panel

[5]The product of the Indirect Effect was computed using the *nlcom* command in Stata, which slightly transforms the standard errors that are shown in the tables above due to variation in how it computes the clustered standard errors.

Table 4.6: Direct and Indirect Effect of EWM on income

EWM variable		Direct Effect	Total difficulties score ...at 8 y/o	Child height ...at 22 y/o	Child test score ...at 19 y/o	Highest educational level ...at 22 y/o	Dropout & child labour bef. 13 y/o ...at 13 y/o
		Ln income: Heckman corrected ...at 22 y/o	Indirect Effect coming from the mediator...				
		Panel A: Rainfall Shocks					
In utero	Above p90	-0.092	0.002	0,005	-0.000	-0.012	0.005
	Below p10	0.019	-0.002	-0,007	0.002	0.022	-0.026**
Infancy	Above p90	0.044	0.001	0,001	0.000	0.028***	-0.021*
	Below p10	0.006	-0.001	0,005	0.001	0.000	-0.014
	N	*710*	*709*	*710*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
		Panel B: Temperature Shocks					
In utero	Above p90	0.059	0.001	0,000	-0.000	-0.008	-0.016
	Below p10	0.212*	0.001	0,003	-0.000	-0.023	0.005
Infancy	Above p90	-0.070	0.001	0,003	0.003	0.005	-0.013
	Below p10	-0.141*	-0.000	-0.000	0.002	0.001	-0.001
	N	*710*	*709*	*710*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Source: self-elaboration based on Young Lives data (Boyden, 2018; Huttly and Jones, 2014).
Note: Clustered standard errors by YL cluster are not shown. * p<0.10, ** p<0.05, *** p<0.01.

A, rainfall EWMs do not affect income directly. However, in Panel B, very cold months seem to directly affect earnings positively if suffered in utero but negatively if suffered during infancy.

What information is derived from the coefficients of the IE rows? Starting with Panel A, rainfall EWM does not affect income through the mediators TDS, child test score and child height. These coefficients are largely non-significant. For the first two mediators (TDS and test score), this absence of indirect effect could have been predicted since Table 4.2, where these two mediators were not affected by rainfall EWMs. However, child height was positively influenced by these EWMs variables (recall the discussion about a possible selection effect above). It seems like this effect is later not translated into income.

In contrast, the educational level and the dropout and child labour mediators display some interesting IEs. To endure very wet months during the first year of life has a *positive* IE on income through the educational level. This contra-intuitive result is another spillover of the labour market characteristics in developing countries. First, the rainfall EWM above the 90^{th} percentile have a large significant negative impact on the educational level ($\hat{\beta} = -0.031^{***}$). Secondly, as described above, YL children with tertiary education are paid worse than those with secondary education, as they have just started their professional careers. Therefore, the educational level has another large significant negative effect on income ($\hat{\theta} = -0.880^{***}$). By multiplying these two negative coefficients, the result is a positive IE. In this sample, one more rainfall EWM above the 90^{th} percentile increases the annual income by 2.8%, this effect coming exclusively from the educational level mediator.

The dropout and child labour variable is the other mediator with significant IEs. In Table 4.2, extremely dry months during gestation and extremely wet ones during infancy has a similar large negative impact on this mediator (respectively,

$\hat{\beta} = -0.051^{***}$ and $\hat{\beta} = -0.040^{***}$). This means that suffering more of these EWMs made the child more prone to abandon school and perform child labour by age 13. In turn, this mediator has a positive impact on labour: those who stayed at school and did not work had much higher income than those who did not stay in school or did work ($\hat{\theta} = -0.827^{**}$). In this case, by multiplying a negative and a positive coefficient, the negative IEs are reached. One more extremely dry month during gestation decreases the annual income by 2.6%. Similarly, one more extremely wet month during the first year of life reduces earnings by 2.1%.

Panel B in Table 4.6 is more relevant for what it does not show than for what it shows. Again, the significant DE of the extremely cold months, either during gestation or in the first year of life, can be seen. However, temperature EWMs do not affect income indirectly through any of the mediators considered. This points towards the fact that with the mediators chosen, it is enough to explore IEs of rainfall EWM, but not for temperature EWM.

The results found in this chapter remarks the title of this dissertation: temperature and rainfall impact children in different ways and through different paths. To ease the understanding of this "climate complexity," Figure 4.1 resumes the most critical effects found. It has to be outlined that if the analysis had stopped at Step 0, this work would have lost much of its potential to explain the effect of climate on income. For example, it would have concluded that there is no effect of rainfall EWM, whereas these shocks have very interesting *Indirect* effects. In short, the Mediation approach has enabled this analysis to go much further.

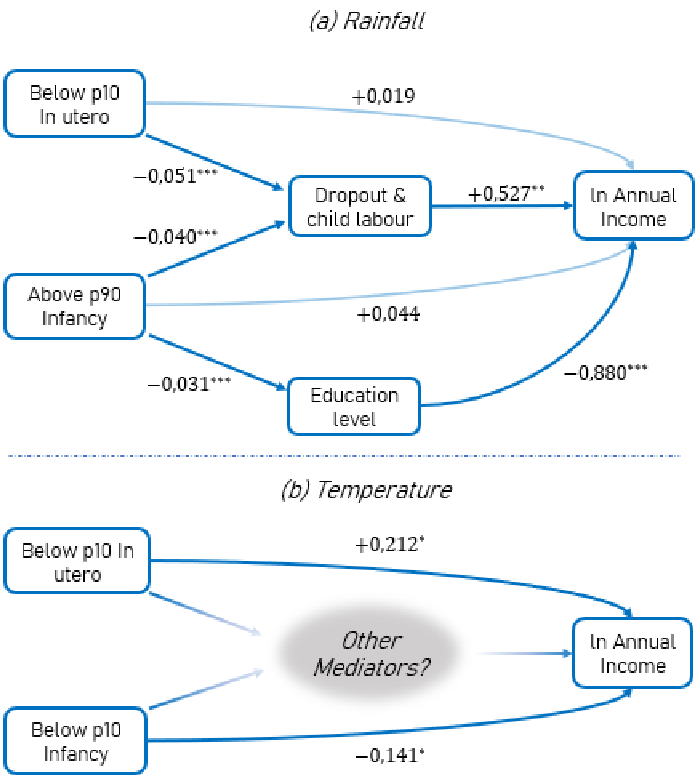

Figure 4.1: ***Summary of some important DEs and IEs found***

Source: self-elaboration.

Note: the faded lines in graph (a) indicates low significance of the DEs.

As it can be seen, the education level and the dropout and child labour mediators proposed in this dissertation are essential to understanding the interplay of climate, education and labour. The implications of these results (and the lack of results in the case of temperature EWMs) are further discussed in Chapter 6.

4.5 Additional analysis: EWM differential effects

Before concluding the Analysis Chapter, some additional gender, trimester of gestation and season of the year insights are added. These extra results aim to enrich the perspective of the Mediation Analysis and help with the interpretation of some of the effects observed above.

Differential effects by gender

Tables A.1 and A.2 report gender differences. These tables portray the EWM effects on mediators (Tables 4.2 and 4.3) and the EWM effects on income including all the mediators (i.e., column 6 of Tables 4.4 and 4.5). This additional analysis is important since the literature reviewed shows differences between boys and girls' adaptation to extreme weather events (Hyland and Russ, 2019; Maccini and Yang, 2009).

Starting with rainfall, the selection effect described above seems to be caused by boys. This is consistent with the medical literature that points out the fact that boys are more vulnerable at early life stages (Kraemer, 2000).

Also, boys' test scores are affected by the number of extreme dry months during gestation, while girls' during infancy. By combining both genders, this effect of EWM on test scores was lost.

The already commented negative effect of extremely wet months during the first year on the educational level comes mainly through the boys. Girls may not be as affected since the number of women who complete the tertiary level is relatively small, regardless of the exposure to climate shocks in early life.

The final mediator has similar implications for both boys and girls. However, EWMs have a slightly higher impact on boys' dropout probability and child labour before age 13. This may signal that girls' chances to abandon school early were already determined by other factors, such as cultural beliefs (Dean and Jayachandran, 2019; Van der Geest, 2010), and the EWM effect is attenuated for women. Specifically, in Andhra Pradesh, the dropout rates in primary school are higher for girls than for boys (Rena, 2007). Finally, as happened when all the sample was considered, rainfall EWMs do not have a DE on income.

If we consider the temperature Table A.2, there are three interesting insights. First, the negative effect of cold months during infancy on height is completely suffered by girls. One more month of these characteristics reduces the height of a girl significantly by 0.45 cm.

Second, boys' and girls' test scores are negatively affected by EWM in the first year of life. However, there is a significant, large and positive effect of extremely warm months for girls. Lastly, the temperature EWMs' effect on income is mainly channelled through boys' income. One extra cold month increases the income by 20% during gestation and decreases it by 20.6% if it is during infancy.

Differential effects by trimester of gestation

Among the fetal origins hypothesis literature, it is common to decompose the pregnancy period between different trimesters of gestation (Rosales-Rueda, 2018; Saulnier and Brolin, 2015). Naturally, only the EWM suffered in utero is considered. The 3rd trimester is the closest to the birth. Tables A.3 and A.4 report in utero trimester differences by rainfall and temperature EWMs respectively.

For rainfall EWMs, no specific trimester can explain a possible selection effect on EWM on heights. Nevertheless, if we perform this trimestral difference only for boys (the ones that seem to be causing it, recall Table A.1), the 1st trimester is positive and significant. Boys that suffered one extra low-temperature month during this trimester are 0.83 cm taller, all things equal (results not reported here). Still, the deceased YL children did not suffer more of this EWM than the living ones. In conclusion, the evidence suggests a selection effect for boys in the 1st trimester. However, with the information available, it is not confirmed.

For test scores, the 1st and 2nd trimesters are the periods of higher sensitivity for the fetus. Finally, for the dropout and child labour mediator, the negative effect found in Table 4.2 seems to come through the shocks suffered in the 1st trimester.

As it can be seen, there is not a trimester where all the significant effects are grouped. Instead, each trimester seems to impact each mediator and the income differently. The reasons behind it stem from the biological and neonatal literature and will be briefly commented on in Chapter 6.

For temperature EWMs, the shocks suffered during the 3rd trimester are responsible for the positive impact of EWM on TDS. This is complex to explain, as some medical articles seem to observe that the psychological stability of the mother during this trimester predicts the behavioural stability of the child (Lundy et al., 1999; Monk et al., 2012). If one assumes that suffering an extremely hot month during the 3rd is a potential stressor for the mother, we should observe a *negative* effect of this EWM variable on the TDS mediator, which does not happen.

Lastly, there are some trimestral effects of temperature EWM on height, test score and the dropout and child labour mediators that did not appear in Table 4.3. In conclusion, by disaggregating the EWM that happened during gestation between trimesters, the view about the impact of climate shocks during the fetal stage has been enriched.

Now we can answer a question that has remained open: why do low temperatures affect fetuses and infants differently? Specifically, very cold months in utero positively impact income, but during infancy, a negative one. In a context of very high temperatures and high humidity, as in Andhra Pradesh, having lower temperatures during gestation can help the mother in the pregnancy process: she gets less tired. Research has found that during the third trimesters, pregnant women's physical activity decays sharply, and lower temperatures may help the mother to continue the physical activity, which is beneficial for the fetus' correct development (Poudevigne and O'Connor, 2006).

However, if Table A.4 is checked, one can see that the positive impact seems to come through the *first* trimester. In Scotland, low temperatures in this trimester of gestation predict higher birthweight (Lawlor et al., 2005), with similar results found in the US (Deschênes et al., 2009; Fishman et al., 2019).

Although the context is completely different, this effect is also found in our sample, at least tangentially. At age 22, those YL children that suffered 3 low-temperature-EWMs during the 1st trimester weight 55.03 kg, while those that suffered 0 EWM weighed 52.8. In short, lower temperatures in utero favours placental stability and the correct development of the child. One of the reasons that no IEs are found for this EWM variable is that the child's correct development might influence multiple mediators, but not strongly any of them. In fact, *all* the coefficients of this variable in Table A.4 are positive, albeit not significant.

On the other hand, why do cold months in infancy have a negative effect? A plausible explanation may come through agriculture. The main crop of the region is rice (Samarpitha et al., 2016). Given that low temperatures reduce rice yields (Saseendran et al., 2000), this may be a possible EWM-income pathway. In our sample, more than one-third of families dedicated to agriculture (N=240) plant rice (N=98), the most common crop. The "rice households" children that suffered more cold months during infancy have lower incomes today. They suffer a "scarring" effect as the life-courses model would say. However, this association is not seen in "non-rice households" [6]. Although this correlation may be spurious, children in "rice households" are more sensitive to low temperatures during infancy. This may be explained because lower temperatures critically affect rice yields, pushing down revenues, nutrition, other mediators, and finally, income. Still, this hypothesis is highly conjectural and has to be the subject of further investigation.

Monsoon differential effects

Finally, an EWM might have differential effects depending on the season of the year. There is a clear division between the wet and dry seasons in the region considered. In the rainy season, between June and September, less rainfall (below the 10th percentile) can cause severe problems for agriculture, as it is at this time that rainfall accumulates to allow agricultural activities in the dry season. On the other hand, heavy rainfall (above the 90th percentile) in these months almost certainly means flooding, as the soil is already soaked and cannot absorb any more water. With this third robustness check, I would only consider those rainfall EWM that occur in the rainy season (monsoon).

Table A.5 reports the rainfall EWMs that happened only during the wet season, from June to September. *Above p90* EWMs during infancy, one of the two variables that were significant in Table 4.2 decreases insignificance, but the size of the coefficients more than doubles.

For the educational level, the impact is increased from $\hat{\beta} = -0.031$ to $\hat{\beta} = -0.062$. For the dropout and child labour mediator, the effect goes from $\hat{\beta} = -0.040$ to $\hat{\beta} = -0.105$. These severe changes go hand with the intuition described above: suffering extreme rainfalls in months that were already extremely wet is most negative for the child.

[6] "Rice household children have suffered between 0 and 5 EWMs of this characteristics, with a mean ln income of 7.85, 8.27, 7.43, 5.29, respectively (last two categories not included due to the low number of observations. "Non-rice" household children have suffered between 0 and 8 EWMs, with a mean ln income of 7.70, 7.42, 6.22, 6.83, 6.79, and 8.14, respectively (last three categories not included due to the low number of observations).

5. Robustness Checks

5.1 Additional definition of EWM

All the results presented above assume that the 90/10 percentile definition is the one that extracts most of the possible effects of EWM over the mediators and the income. However, how do these impacts change if we vary the definition of EWM?

Dummy definition of EWM

First, instead of considering a continuous definition for EWM, a dummy alternative is made: 1 if the EWM was suffered by the YL child and 0 otherwise. This also controls for the accumulation of temperature EWM at the ends of the distribution (recall (b) and (d) graphs in Figure 3.6). Table B.1 shows the computation of the Direct and Indirect Effects. This table is analogous to Table 4.6 in Step 3 [1].

With the dummy definition, it is clear that results change drastically. Before, rainfall EWM did not have a DE on income, while temperature EWM (in utero below p10 and up to 1 y/o below p10) did have a DE. Now, it is rainfall the one that has a strongly significant DE on income. Having suffered at least one extremely wet month during infancy decreases income sharply by 78.5%. On the other hand, to have suffered at least one extremely dry month, also during the first year of life, increases income by 74.5%. Additionally, the IEs that rainfall had over income through the mediators in the 90/10 definition disappeared with the dummy one.

In a first view, this may indicate that temperature EWM impacts cumulatively (not significant when dummies, significant in the 90/10 original variables). In contrast, once a YL child has suffered a rainfall EWM, the following do not have an effect (they are more significant when the dummies are considered, but not in the original, continuous variable).

However, the extreme results (−78.5% and +74.5%) are partially explained by the extreme compression that a dummy specification supposes in this context. Given the distribution of rainfall shocks (recall Figure 3.5), with some children suffering up to 8 or 9 of them, the dummy definition assumes that children with 1 shock or with 9 suffered the same. Many children have suffered both rainfall EWM above p90 *and* below p10 during infancy (340 out of the 710 individuals). These large and highly significant results may be exacerbating small trends and cancelling each other since almost half of the sample has suffered both types of EWMs. In short, a continuous specification for the EWM variables was more appropriate.

[1] For reasons of space and simplicity, not all the tables in Chapter 4 have been replicated with this new definition.

80/20 criteria for EWM

Still, is the 90/10 criteria the correct one to extract the impact of EWM? Furthermore, how does the picture described above change if we alter the selection of percentiles?.

The first alternative criteria is the 80/20 definition, meaning that months above the 80^{th} or below the 20^{th} percentiles are considered EWM. This is the criteria that other studies related to this dissertation have considered for their definition of extreme weather events (Jayachandran, 2006; Kaur, 2019; Shah and Steinberg, 2017).

Table B.2 in Appendix A shows the results for the Step 3 using the 80/20 criteria. Comparing it with Table 4.6 the significance of the coefficients decay, especially in Panel B (temperature). For example, rainfall EWMs above p90 had a positive IE on income through the education level mediator of 2.8%, while now, EWMs above p80 same IE is 2%.

The intuition described in Chapter 3 seems to be certain: broadening the scope for EWM also leaves the door open for possible attenuation effects. Months between the 80^{th} and 90^{th} or between the 20^{th} and 10^{th} percentiles are simply not that "extreme" and reduce the impact of climate shocks at early life on income and the mediators.

95/05 criteria for EWM

The final criterion considered is the even more restrictive 95/05 threshold. In theory, this definition of EWM should create "sharper" results. Table B.3 provides the computation of the Direct and Indirect Effects (Step 3). In Panel A (rainfall), the coefficients that were already significant in Table 4.6 (i.e., the IEs coming from the educational level and dropout and child labour mediators) have a more prominent size with the 95/05 criteria.

However, in Panel B, the previously significant DEs in the 90/10 table now have much lower coefficients and are even less significant than with the 80/20 criteria. For this subsample, the 90/10 definition seems to "maximize" the impact of temperature EWM in early life. For the two significant variables (cold months during gestation and infancy), there are differential effects at the end of the distribution. This means that "extremely extreme" cold months (e.g., 99^{th} percentile) have a different impact than "just-extreme" months (e.g., 91^{th} percentile). These marginal differences in the distribution of temperature shocks do not appear in the rainfall panel, as the coefficients are more stable regardless of the criteria that we choose (80/20, 90/10 or 95/05). The rainfall distribution of shocks is less sensitive to changes in the EWM definition, whereas temperature is more unstable.

5.2 Additional income threshold

This final robustness check changes the selected/non-selected criteria for the Heckman correction model. Prior, all the YL children that worked were considered as selected, although many of them were unpaid (recall Figure 3.7). The non-selected individuals were those with no recorded work activity.

Here, the individuals that work but are unpaid ($lntotinc = 0$) are also considered non-selected. Instead of having 427 "selected" individuals, this figure is reduced to

334 with this new definition.

The results for this specification are presented in Table C.1. The DE of temperature EWM ceases to be significant, although the signs remain the same. For rainfall EWM, the significance is lost in the dropout and child labour mediator. Additionally, the IE of extremely warm EWM during infancy goes from 2.8% to 1.5% but maintains its significance.

It is clear that considering the unpaid workers as non-selected observations change significantly the results shown above. Most of the significant effects (DEs of temperature EWMs and IEs of rainfall EWMs through the dropout mediator) emerged in the base specification.

The critical question, therefore, is which specification is the correct one. The literature reviewed about labour markets in developing countries outlines that there is a sizeable part of the *active and working* population that is unpaid. This is due to various reasons: family business that pay in kind, self-employment, irregular payments, etc. (Fox and Kaul, 2018; Fields, 2011; Van der Geest, 2010; Fares et al., 2006; Msigwa and Kipesha, 2013). Thus, this dissertation regards more reasonable the base specification as this robustness check would ignore a palpable reality in developing countries' labour markets.

6. Discussion

First of all, have the Questions posed in this dissertation been answered? Question 1 inquired if the *early life extreme weather events affect young adults' labour income*. With the information available, rainfall EWMs in early life do not seem to have *Direct* effects on income. On the other hand, temperature EWMs do have *Direct* effects, concretely very cold months during gestation and in utero.

Then, Question 2 tried to disentangle *through which pathways does exposure to extreme weather events in early life affect young adults' labour income?*. Rainfall and temperature EWM impact the mediators chosen in multiple ways. However, those IEs that prevail are rainfall EWMs impacting income through educational level and early school dropout and child labour.

The answer to the second question outlines the importance of the Mediation Analysis to study the complex effects of early life climate shocks on children and their later income. If one had left the analysis in Step 0, the conclusions would not have been wrong, but several interesting nuances would have been lost.

Rainfall and education

Existing evidence seems to underline that individuals that suffered early life droughts have worse socioeconomic status, mainly reflected due to lack of educational attainment (Hyland and Russ, 2019; Shah and Steinberg, 2017; Maccini and Yang, 2009). These results are partially found in this dissertation. The educational level and dropout and child labour mediators are indeed the ones that portray higher significance. For example, low rainfall in utero reduces the possibility of the children staying in education and not performing child labour until age 13, in line with previous research.

However, high rainfall during infancy reduces educational outcomes, which would go against the evidence at first glance. Nevertheless, one has to consider the differences between the definitions of EWE. Most articles use deviations from the long-run means. In contrast, this dissertation uses the *distribution* of past years, applying the 90/10 thresholds. Deviations from the mean might be enough if the primary mechanism at play is agricultural output (i.e., more rainfall, more crops, higher seasonal income and better nutrition for the infant) as many authors pose (Hyland and Russ, 2019; Maccini and Yang, 2009; Shah and Steinberg, 2017). However, the 90/10 definition implies a higher severity that may undermine the agricultural mechanism. Other literature that studies extreme rainfall episodes like monsoons would accommodate more to this negative impact of extremely wet months on education (Rosales-Rueda, 2018).

Temperature issues

The literature review stated that articles that study early life climate shocks tend to focus on several socioeconomic outcomes. In contrast, the ones that focus on temperature use actual labour income as the primary outcome (Deschênes et al., 2009; Isen et al., 2017; Fishman et al., 2019). They find that higher temperatures in utero reduce adult income. The results presented in this dissertation do not find that effect: low-temperature months are the ones affecting income.

The specific socio-climatic environment of the location studied, and the definitions of weather shocks are most likely behind the differences between this work and the previous literature. Still, it underlines the possibility that low temperatures also play a role in the development of fetuses and children. In addition, no mediator seems to add IEs from temperature on income, even though the set of variables chosen is quite broad. Both observations represent more future research lines.

Climate and work experience

The more educated you are in this sample, the lower your earnings. The problems of young people in developing countries' labour markets have been already presented above. At the beginning, education does not ensure you better earnings (Fox and Kaul, 2018; Fields, 2011; Van der Geest, 2010; Fares et al., 2006; Msigwa and Kipesha, 2013). Nevertheless, when this negative effect goes away? In other words, when do the returns of education surpass the fact that tertiary-educated YL children started working after the rest? In the future, what could be the IE of EWMs on the YL children through education, once the labour income is net of this "high education but low experience" effect?

Thanks to Step 1, the answer seems straightforward. EWM negatively affect education, and this will still be the case after the years have passed since, after age 22, there are only small changes in educational attainment. This dissertation hypothesises that after a few years have passed, education returns will overcome this "late start penalty". Then, the IE will turn negative, as higher education will suddenly predict higher income (negative β times positive θ). In developing countries, these returns are high (O'Higgins, 2003; Psacharopoulos and Patrinos, 2002). In a fast-paced economy like India, the educated population will be better positioned to extract the most out of the structural transformation from agriculture to services, a process that India is currently immersed in. To find the exact moment when the returns surpass the lack of experience is another research line.

Policy implications

Andhra Pradesh has an outstanding mortality due to extreme weather events. Although it has decayed sharply in the last decades, it is still the highest among the bigger states in India (Ray et al., 2021). This should give a perspective on what remains to be done in natural disaster prevention. Nevertheless, after the shock has passed, the exposed population continues to need institutional support.

With the evidence gathered in this dissertation, authorities should be most concerned about education, child labour, and youth labour market integration. However, contrary to victims of specific major weather shocks, the "victims" of the EWM are more difficult to identify. Therefore, policies are harder to target. As usual, access to education must be protected. Specifically, families forced to withdraw their children from school and into child labour must be supported. At least these kinds of policies were put in place decades ago, but for other reasons. A spillover effect of these policies might be to reduce the impact of early life weather shocks on education and child labour, and ultimately, income.

Given that temperature seems to affect income directly, other measures can be aimed at improving the insulation of houses, which other studies have found to be beneficial (Isen et al., 2017). Finally, labour markets should accommodate the increasingly better-educated workforce, although this is a slow-moving process.

6.1 Limitations

The main drawback of this dissertation is its small sample. These results are complicated to generalise to India or the rest of the developing countries. Indeed, the pro-rich design of the YL in India complicates the generalisation even to the state of Andhra Pradesh. How may results have changed with a more balanced sample? For example, the selection effect of rainfall shocks on heights (Table 4.2) might be greater, as poorer households may have lost more weak fetuses and infants.

Regarding the other data source, the UDel database provides a reliable historical measure of weather across the globe. However, other databases have slightly better resolutions, which could reduce the measurement error.

Another limitation is that shocks that happened before pregnancy are not considered. Those YL children that lived in areas that suffered shocks in the previous year *and* suffered a shock during their gestation may have been more affected than those children that lived in areas with typical weather in the last years but then suffered one EWM sporadically during gestation.

Finally, the correlation between mediators has been addressed, but not the timeline. In Mediation analyses with multiple mediators, if one needs to infer causality, the moment at which the mediator is measured is important. Nevertheless, the analysis in this dissertation was not designed for that purpose. In future work, the relationship between mediators should be further explored.

7. Conclusion

This dissertation has applied the fetal origins hypothesis and other concepts from life-course models to understand how early life weather shocks affect children in multiple areas and, ultimately, on early labour income. Many results have been commented on previously. Here, the most important ones are highlighted.

For our sample considered here, rainfall and temperature EWM impact the set of mediators chosen differently. Rainfall shocks affect heights, educational level and child labour decisions. On the other hand, temperature shocks have stronger effects on the psychological and, primarily, the cognitive level of YL children.

Suffering one extra cold month in utero directly increases income significantly by 21.2%. This seems to be caused by the placental stability that low temperatures allow. The below p10 EWM variable has a positive effect on all the mediators. In a context of high temperatures and humidity, having milder temperatures might help in the gestation period, which is later translated into a better development during childhood.

On the other hand, cold months during infancy directly reduce income significantly by 14.1%. In this case, the evidence suggests that low temperatures may harm agricultural production, reducing the income of the YL households and harming the YL children. Specifically, the children coming from rice-farming families are the ones that are "scarred", as the life-courses model would say.

Another striking result is that the mediators chosen here do not generate temperature IEs on income. Future research would need to address the pathways that temperature shocks follow to impact income.

One of the main contributions of this dissertation is the empirical application of the Mediation Analysis. Again, if the analysis had stopped at Step 0, this work would have lost much of its potential to explain the effect of climate on income. For example, it would have concluded that there is no effect of rainfall EWM on income, whereas these shocks have three very interesting Indirect effects.

First, one more rainfall EWM above the 90th percentile increases the annual income by 2.8%, this effect coming exclusively from the educational level mediator. This is due to the "late penalty start" that educated individuals suffer when they begin their professional careers. Second, one more extremely dry month during gestation decreases the annual income by 2.6% through the dropout and child labour mediators. Third, one more extremely wet month during the first year of life reduces earnings by 2.1%, also through this mediator. In short, the Mediation approach has enabled this analysis to go much further, helping to prove that child labour is something that future research on early life weather shocks needs to consider.

The additional analysis depending on gender, trimester of gestation and season of the year enhances the understanding of how early life weather shocks affect children. For example, the selection effect that is described above seems to be caused by boys during the 1st trimester of gestation. Moreover, boys' income seems the one affected by early life temperature EWMs.

The continuous EWM definition is deemed a better specification than the dummy one in the robustness checks. Also, this dissertation observes that the rainfall distribution of shocks is less sensitive to changes in the EWM definition (80/10, 90/10, 95/05), whereas the temperature one is more unstable.

Given that extreme weather events are likely to increase in the following decades, it is mandatory to understand how climate affects humans. The results showed in this dissertation confirm the critical role of early life weather shocks in later life outcomes. What can be done to protect children? The answer is multifaceted but points directly to the crucial part played by educational outcomes and early child labour. The good news is that most emerging countries have been focusing their developmental policies on those areas for several decades. By pushing harder in that direction, most of the Indirect Effects of early life rainfall shocks will attenuate.

Even so, humanity will never be free from the effects of climate. This work has seen how shocks early in life have medium- and long-term effects. The policies involved should not only go in one direction when it comes to improving individuals' adaptation to climate. Instead, the approach should be multidimensional, as we have seen that the effects are also multidimensional.

Bibliography

Acosta, A., Nicolli, F. and Karfakis, P. (2021), 'Coping with climate shocks: The complex role of livestock portfolios', *World Development* **146**, 105546.

Aguilar, A. and Vicarelli, M. (2011), 'El Niño and Mexican children: medium-term effects of early-life weather shocks on cognitive and health outcomes', *Cambridge, United States: Harvard University, Department of Economics. Manuscript* .

Alderman, H., Hoddinott, J. and Kinsey, B. (2006), 'Long term consequences of early childhood malnutrition', *Oxford economic papers* **58**(3), 450–474.

Almond, D. (2006), 'Is the 1918 influenza pandemic over? long-term effects of in utero influenza exposure in the post-1940 US population', *Journal of political Economy* **114**(4), 672–712.

Almond, D. and Currie, J. (2011), 'Killing me softly: The fetal origins hypothesis', *Journal of economic perspectives* **25**(3), 153–72.

Auffhammer, M., Hsiang, S. M., Schlenker, W. and Sobel, A. (2020), 'Using weather data and climate model output in economic analyses of climate change', *Review of Environmental Economics and Policy* .

Baird, S., Friedman, J. and Schady, N. (2011), 'Aggregate income shocks and infant mortality in the developing world', *Review of Economics and statistics* **93**(3), 847–856.

Baland, J.-M. and Robinson, J. A. (2000), 'Is child labor inefficient?', *Journal of political economy* **108**(4), 663–679.

Barker, D. J. (2001), 'Fetal and infant origins of adult disease', *Monatsschrift Kinderheilkunde* **149**(1), S2–S6.

Barker, D. J. and Osmond, C. (1986), 'Infant mortality, childhood nutrition, and ischaemic heart disease in england and wales', *The Lancet* **327**(8489), 1077–1081.

Baron, R. M. and Kenny, D. A. (1986), 'The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations.', *Journal of personality and social psychology* **51**(6), 1173.

Bartlett, S. (2008), 'The implications of climate change for children in lower-income countries', *Children Youth and Environments* **18**(1), 71–98.

Basu, K. and Van, P. H. (1998), 'The economics of child labor', *American economic review* pp. 412–427.

Beegle, K., Dehejia, R. and Gatti, R. (2009), 'Why should we care about child labor? the education, labor market, and health consequences of child labor.', *Journal of Human Resources* **44**(4), 871–889.

Beegle, K., Dehejia, R. H. and Gatti, R. (2006), 'Child labor and agricultural shocks', *Journal of Development economics* **81**(1), 80–96.

Ben-Shlomo, Y. and Kuh, D. (2002), 'A life course approach to chronic disease epidemiology: conceptual models, empirical challenges and interdisciplinary perspectives', *International journal of epidemiology* **31**(2), 285–293.

Bengtsson, T., Campbell, C., Lee, J. Z. et al. (2004), *Life under pressure: Mortality and living standards in Europe and Asia, 1700-1900*, Mit Press.

Berkman, L. F. (2009), 'Social epidemiology: social determinants of health in the United States: are we losing ground?', *Annual review of public health* **30**, 27–41.

Besley, T. (1994), 'How do market failures justify interventions in rural credit markets?', *The World Bank Research Observer* **9**(1), 27–47.

Bhalotra, S. and Heady, C. (2003), 'Child farm labor: The wealth paradox', *The World Bank Economic Review* **17**(2), 197–227.

Binswanger, H. and Rosenzweig, M. (1993), 'Wealth, weather risk and the composition and profitability of agricultural investments', *Economic Journal* **103**(416), 56–78.

Blau, D. M. (1985), 'Self-employment and self-selection in developing country labor markets', *Southern Economic Journal* pp. 351–363.

Boozer, M. and Suri, T. (2001), 'Child labor and schooling decisions in Ghana', *Mimeograph, Yale University* .

Boyden, J. (2018), 'Young Lives: an international study of childhood poverty: Rounds 1-5 constructed files, 2002-2016.[data collection]', *3 rd Editi on. UK Data Service. SN* **7483**.

Briones, K. (2017), 'How many rooms are there in your house? Constructing the Young Lives wealth index', *Young Lives Technical Note* **43**.

Briones, K. (2018), 'A guide to Young Lives rounds 1 to 5 constructed files', *Young Lives Technical Note* **48**, 1–31.

Burke, S. E., Sanson, A. V. and Van Hoorn, J. (2018), 'The psychological effects of climate change on children', *Current psychiatry reports* **20**(5), 1–8.

Chant, S. and Pedwell, C. (2008), 'Women, gender and the informal economy: An assessment of ILO research and suggested ways forward'.

Chaudhuri, S. and Paxson, C. (2001), 'Smoothing consumption under income seasonality: buffer stocks vs. credit', *Colombia University, Department of Economics, Discussion Paper Series* .

Clayton, S., Manning, C., Krygsman, K., Speiser, M. et al. (2017), 'Mental health and our changing climate: Impacts, implications, and guidance', *Washington, DC: American Psychological Association and ecoAmerica* .

Dean, G. and Kurtzke, J. F. (1971), 'On the risk of multiple sclerosis according to age at immigration to South Africa', *Br Med J* **3**(5777), 725–729.

Dean, J. T. and Jayachandran, S. (2019), Changing family attitudes to promote female employment, *in* 'AEA Papers and Proceedings', Vol. 109, pp. 138–42.

Dell, M., Jones, B. F. and Olken, B. A. (2009), 'Temperature and income: reconciling new cross-sectional and panel estimates', *American Economic Review* **99**(2), 198–204.

Dell, M., Jones, B. F. and Olken, B. A. (2012), 'Temperature shocks and economic growth: Evidence from the last half century', *American Economic Journal: Macroeconomics* **4**(3), 66–95.

Dercon, S. (2006), 'Vulnerability: a micro perspective', *Securing development in an unstable world* **30**, 117–146.

Deryugina, T. and Hsiang, S. M. (2014), Does the environment still matter? Daily temperature and income in the United States, Technical report, National Bureau of Economic Research.

Deschênes, O., Greenstone, M. and Guryan, J. (2009), 'Climate change and birth weight', *American Economic Review* **99**(2), 211–17.

Dockery, D. W., Pope, C. A., Xu, X., Spengler, J. D., Ware, J. H., Fay, M. E., Ferris Jr, B. G. and Speizer, F. E. (1993), 'An association between air pollution and mortality in six US cities', *New England journal of medicine* **329**(24), 1753–1759.

Dornan, P., Ogando Portela, M. J. and Pells, K. (2014), *Climate Shocks, Food and Nutrition Security: Evidence from the Young Lives cohort study*, Oxfam International.

Dreze, J. and Sen, A. (1990), *Hunger and public action*, Clarendon Press.

Emerson, P. M. and Souza, A. P. (2011), 'Is child labor harmful? the impact of working earlier in life on adult earnings', *Economic development and cultural change* **59**(2), 345–385.

Enders, C. K. (2010), *Applied missing data analysis*, Guilford press.

Ezra, M. and Kiros, G.-E. (2000), 'Household vulnerability to food crisis and mortality in the drought-prone areas of northern ethiopia', *Journal of biosocial science* **32**(3), 395–409.

Fares, J., Montenegro, C. E. and Orazem, P. F. (2006), 'How are youth faring in the labor market? Evidence from around the world', *Evidence from Around the World (November 1, 2006). World Bank Policy Research Working Paper* (4071).

Fields, G. S. (2011), 'Labor market analysis for developing countries', *Labour economics* **18**, S16–S22.

Fishman, R., Carrillo, P. and Russ, J. (2019), 'Long-term impacts of exposure to high temperatures on human capital and economic productivity', *Journal of Environmental Economics and Management* **93**, 221–238.

Fox, L. and Kaul, U. (2018), 'The evidence is in: How should youth employment programs in low-income countries be designed?', *World Bank Policy Research Working Paper* (8500).

Giné, X., Townsend, R. and Vickery, J. (2008), 'Patterns of rainfall insurance participation in rural india', *The World Bank Economic Review* **22**(3), 539–566.

GOI (2012), 'The child marriage restraint act of 1929', *Government of India* .

Gunnarsson, V., Orazem, P. F. and Sánchez, M. A. (2006), 'Child labor and school achievement in Latin America', *The World Bank Economic Review* **20**(1), 31–54.

Hanna, R. and Oliva, P. (2016), 'Implications of climate change for children in developing countries', *The Future of Children* pp. 115–132.

Hansen, J., Johnson, D., Lacis, A., Lebedeff, S., Lee, P., Rind, D. and Russell, G. (1981), 'Climate impact of increasing atmospheric carbon dioxide', *Science* **213**(4511), 957–966.

Harris, J. R. and Todaro, M. P. (1970), 'Migration, unemployment and development: a two-sector analysis', *The American economic review* **60**(1), 126–142.

Heady, C. (2003), 'The effect of child labor on learning achievement', *World Development* **31**(2), 385–398.

Heckman, J. J. (1979), 'Sample selection bias as a specification error', *Econometrica: Journal of the econometric society* pp. 153–161.

Hertel, T. W. and Rosch, S. D. (2010), 'Climate change, agriculture, and poverty', *Applied economic perspectives and policy* **32**(3), 355–385.

Hsiang, S. M., Burke, M. and Miguel, E. (2013), 'Quantifying the influence of climate on human conflict', *Science* **341**(6151), 1235367.

Huttly, S. and Jones, N. (2014), 'Young Lives: an international study of childhood poverty: Round 1, 2002', *UK Data Service. SN* **5307**.

Hyland, M. and Russ, J. (2019), 'Water as destiny–the long-term impacts of drought in sub-saharan africa', *World Development* **115**, 30–45.

Ilahi, N., Orazem, P. and Sedlacek, G. (2000), 'The implications of child labor for adult wages, income and poverty: retrospective evidence from Brazil', *The World Bank* .

ILO (2018), 'India wage report: Wage policies for decent work and inclusive growth', *India: International Labor Organization* .

Isen, A., Rossin-Slater, M. and Walker, R. (2017), 'Relationship between season of birth, temperature exposure, and later life wellbeing', *Proceedings of the National Academy of Sciences* **114**(51), 13447–13452.

Jayachandran, S. (2006), 'Selling labor low: Wage responses to productivity shocks in developing countries', *Journal of political Economy* **114**(3), 538–575.

Johnston, D. W., Schurer, S. and Shields, M. A. (2013), 'Exploring the intergenerational persistence of mental health: Evidence from three generations', *Journal of health economics* **32**(6), 1077–1089.

Judge, T. A. and Cable, D. M. (2004), 'The effect of physical height on workplace success and income: preliminary test of a theoretical model.', *Journal of Applied Psychology* **89**(3), 428.

Kaczan, D. J. and Orgill-Meyer, J. (2020), 'The impact of climate change on migration: a synthesis of recent empirical insights', *Climatic Change* **158**(3), 281–300.

Kaur, S. (2019), 'Nominal wage rigidity in village labor markets', *American Economic Review* **109**(10), 3585–3616.

Kellenberg, D. K. and Mobarak, A. M. (2008), 'Does rising income increase or decrease damage risk from natural disasters?', *Journal of urban economics* **63**(3), 788–802.

Kertes, D. A., Bhatt, S. S., Kamin, H. S., Hughes, D. A., Rodney, N. C. and Mulligan, C. J. (2017), 'Bndf methylation in mothers and newborns is associated with maternal exposure to war trauma', *Clinical epigenetics* **9**(1), 1–12.

Kraemer, S. (2000), 'The fragile male', *BMJ (Clinical research ed.)* **321**(7276), 1609–1612.

Kuczmarski, R. J. (2002), *2000 CDC Growth Charts for the United States: methods and development*, number 246, Department of Health and Human Services, Centers for Disease Control and . . . .

Kumra, N. (2008), 'An assessment of the Young Lives sampling approach in Andhra Pradesh, India', *Young Lives Technical Note* **2**.

Kuznets, S. (1955), 'Economic growth and income inequality', *The American economic review* **45**(1), 1–28.

Lawlor, D. A., Leon, D. A. and Smith, G. D. (2005), 'The association of ambient outdoor temperature throughout pregnancy and offspring birthweight: findings from the Aberdeen children of the 1950s cohort', *BJOG: An International Journal of Obstetrics & Gynaecology* **112**(5), 647–657.

Lewis, W. A. (1954), 'Economic development with unlimited supplies of labour'.

Lindeboom, M., Portrait, F. and Van den Berg, G. J. (2010), 'Long-run effects on longevity of a nutritional shock early in life: the dutch potato famine of 1846–1847', *Journal of health economics* **29**(5), 617–629.

Lundy, B. L., Jones, N. A., Field, T., Nearing, G., Davalos, M., Pietro, P. A., Schanberg, S. and Kuhn, C. (1999), 'Prenatal depression effects on neonates', *Infant behavior and development* **22**(1), 119–129.

Maccini, S. and Yang, D. (2009), 'Under the weather: Health, schooling, and economic consequences of early-life rainfall', *American Economic Review* **99**(3), 1006–26.

Masten, A. S. (2001), 'Ordinary magic: Resilience processes in development.', *American psychologist* **56**(3), 227.

Mendelsohn, R. (2009), 'The impact of climate change on agriculture in developing countries', *Journal of Natural Resources Policy Research* **1**(1), 5–19.

Mendelsohn, R., Nordhaus, W. D. and Shaw, D. (1994), 'The impact of global warming on agriculture: a ricardian analysis', *The American economic review* pp. 753–771.

MHRD (2014), 'Educational statistics at a glance.', *Ministry of Human Resources and Development, Government of India* .

Mohanty, M. (2006), 'Challenges of revolutionary violence: The Naxalite movement in perspective', *Economic and Political Weekly* pp. 3163–3168.

Monk, C., Spicer, J. and Champagne, F. A. (2012), 'Linking prenatal maternal adversity to developmental outcomes in infants: the role of epigenetic pathways', *Development and psychopathology* **24**(4), 1361–1376.

Montez, J. K. and Hayward, M. D. (2011), Early life conditions and later life mortality, *in* 'International handbook of adult mortality', Springer, pp. 187–206.

Msigwa, R. and Kipesha, E. F. (2013), 'Determinants of youth unemployment in developing countries: Evidences from tanzania', *Journal of Economics and Sustainable Development* **4**(14), 67–76.

NASA (2015), 'What's the difference between weather and climate?'.
URL: $https://www.nasa.gov/mission_pages/noaa-n/climate/climate_weather.html$

No, F., Sam, C. and Hirakawa, Y. (2012), 'Revisiting primary school dropout in rural Cambodia', *Asia Pacific Education Review* **13**(4), 573–581.

No, F., Taniguchi, K. and Hirakawa, Y. (2016), 'School dropout at the basic education level in rural Cambodia: Identifying its causes through longitudinal survival analysis', *International Journal of Educational Development* **49**, 215–224.

Nordhaus, W. D. (1991), 'To slow or not to slow: the economics of the greenhouse effect', *The economic journal* **101**(407), 920–937.

O'Higgins, N. (2003), 'Trends in the youth labour market in developing and transition countries', *World Bank Social Protection Discussion Paper Series* (0321).

Orlowsky, B. and Seneviratne, S. I. (2012), 'Global changes in extreme events: regional and seasonal dimension', *Climatic Change* **110**(3), 669–696.

Palloni, A. (2006), 'Reproducing inequalities: Luck, wallets, and the enduring effects of childhood health', *Demography* **43**(4), 587–615.

Panagariya, A. and Mukim, M. (2014), 'A comprehensive analysis of poverty in india', *Asian Development Review* **31**(1), 1–52.

Patrinos, H. A. and Psacharopoulos, G. (1997), 'Family size, schooling and child labor in peru–an empirical analysis', *Journal of population economics* **10**(4), 387–405.

Pells, K. (2011), 'Poverty, risk and families' responses: Evidence from Young Lives'.

Poudevigne, M. S. and O'Connor, P. J. (2006), 'A review of physical activity patterns in pregnant women and their relationship to psychological health', *Sports medicine* **36**(1), 19–38.

Preston, S. H., Hill, M. E. and Drevenstedt, G. L. (1998), 'Childhood conditions that predict survival to advanced ages among African–Americans', *Social science & medicine* **47**(9), 1231–1246.

Pruss-Ustun, A., Corvalán, C. F., Organization, W. H. et al. (2006), *Preventing disease through healthy environments: towards an estimate of the environmental burden of disease*, World Health Organization.

Psacharopoulos, G. and Patrinos, H. A. (2002), 'Returns to investment in education: a further update', *Policy Research Working Paper* **2881**.

Ray, K., Giri, R., Ray, S., Dimri, A. and Rajeevan, M. (2021), 'An assessment of long-term changes in mortalities due to extreme weather events in india: A study of 50 years' data, 1970–2019', *Weather and Climate Extremes* **32**, 100315.

Rena, R. (2007), 'Factors affecting the enrollment and the retention of students at primary education in Andhra Pradesh - a village level study', *Essays in Education* **22**, 102–112.

Rosales-Rueda, M. (2018), 'The impact of early life shocks on human capital formation: Evidence from El Niño floods in Ecuador', *Journal of health economics* **62**, 13–44.

Rosenzweig, M. R. (1980), 'Neoclassical theory and the optimizing peasant: An econometric analysis of market family labor supply in a developing country', *The Quarterly Journal of Economics* **94**(1), 31–55.

Ross, C. E. and Wu, C.-l. (1995), 'The links between education and health', *American sociological review* pp. 719–745.

Samarpitha, A., Vasudev, N. and Suhasini, K. (2016), 'Socio-economic characteristics of rice farmers in the combined state of Andhra Pradesh', *Asian Journal of Agricultural Extension, Economics & Sociology* **13**(1), 1–9.

Saseendran, S., Singh, K., Rathore, L., Singh, S. and Sinha, S. (2000), 'Effects of climate change on rice production in the tropical humid climate of Kerala, India', *Climatic Change* **44**(4), 495–514.

Saulnier, D. D. and Brolin, K. (2015), ‘A systematic review of the health effects of prenatal exposure to disaster’, *International journal of public health* **60**(7), 781–787.

Shah, M. and Steinberg, B. M. (2017), ‘Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital’, *Journal of Political Economy* **125**(2), 527–561.

Sheffield, P. E. and Landrigan, P. J. (2011), ‘Global climate change and children’s health: threats and strategies for prevention’, *Environmental health perspectives* **119**(3), 291–298.

Syrén, S. M., Kokko, K., Pulkkinen, L. and Pehkonen, J. (2020), ‘Income and mental well-being: personality traits as moderators’, *Journal of Happiness Studies* **21**(2), 547–571.

Tiwari, S., Jacoby, H. G. and Skoufias, E. (2017), ‘Monsoon babies: Rainfall shocks and child nutrition in Nepal’, *Economic Development and Cultural Change* **65**(2), 167–188.

Tubiello, F. N. and Rosenzweig, C. (2008), ‘Developing climate change impact metrics for agriculture’, *Integrated Assessment Journal* **8**(1).

Van der Geest, K. (2010), ‘Rural youth employment in developing countries: A global view’, *FAO Gender, Equity and Rural Employment Division* .

Van Os, J. and Selten, J.-P. (1998), ‘Prenatal exposure to maternal stress and subsequent schizophrenia: the may 1940 invasion of the Netherlands’, *The british journal of psychiatry* **172**(4), 324–326.

VanderWeele, T. (2015), *Explanation in causal inference: methods for mediation and interaction*, Oxford University Press.

VanderWeele, T. J. (2012), ‘Invited commentary: structural equation models and epidemiologic analysis’, *American journal of epidemiology* **176**(7), 608–612.

VanderWeele, T. J. (2016), ‘Mediation analysis: a practitioner’s guide’, *Annual review of public health* **37**, 17–32.

VanderWeele, T. and Vansteelandt, S. (2014), ‘Mediation analysis with multiple mediators’, *Epidemiologic methods* **2**(1), 95–115.

Walder, D. J., Laplante, D. P., Sousa-Pires, A., Veru, F., Brunet, A. and King, S. (2014), ‘Prenatal maternal stress predicts autism traits in 61/2 year-old children: Project Ice Storm’, *Psychiatry research* **219**(2), 353–360.

Whitehead, R. (1985), ‘The human weaning process’, *Pediatrics* **75**(1), 189–193.

Wilde, J., Apouey, B. H. and Jung, T. (2017), ‘The effect of ambient temperature shocks during conception and early pregnancy on later life outcomes’, *European Economic Review* **97**, 87–107.

Willmott, C. J. and Matsuura, K. (2001), 'Terrestrial air temperature and precipitation: Monthly and annual time series (1950 - 1999)', *WWW url: http://climate.geog.udel.edu/ climate/html*$_p$*ages/README.ghcn*$_t$*s2.html*.

Wolfolds, S. E. and Siegel, J. (2019), 'Misaccounting for endogeneity: The peril of relying on the Heckman two-step method without a valid instrument', *Strategic Management Journal* **40**(3), 432–462.

Wright, T. A. and Cropanzano, R. (2004), 'The role of psychological well-being in job performance:: a fresh look at an age-old quest', *Organizational dynamics* **33**(4), 338–351.

Xu, Z., Etzel, R. A., Su, H., Huang, C., Guo, Y. and Tong, S. (2012), 'Impact of ambient temperature on children's health: a systematic review', *Environmental research* **117**, 120–131.

YL (2017), 'Young Lives survey design and sampling (round 5): United Andhra Pradesh'.

YL (2018*a*), 'Young Lives survey design and sampling (round 5): Ethiopia'.

YL (2018*b*), 'Young Lives survey design and sampling (round 5): Peru'.

YL (2018*c*), 'Young Lives survey design and sampling (round 5): Vietnam'.

YL (2022), 'Home page: Young-lives'.
URL: *https://www.younglives.org.uk/*

Zivin, J. G. and Shrader, J. (2016), 'Temperature extremes, health, and human capital', *The Future of Children* pp. 31–50.

A. EWM differential effects

In each of the following tables the first five columns are analogous to the Tables of Step 1. The last column is analogous to the Tables of Step 2, although the coefficients of the mediators are not shown. For girls, the Heckman correction was not computed as the low number of observations made the selection equation (a Probit model) not converging. Results for the computation of DEs and IEs are not shown.

Table A.1: Early-life rainfall EWM effect on mediators and income, by gender

		Dependant variables						
		Total difficulties score	Child height	Child test score	Highest educational level	Dropout & child labour bef. 13 y/o	Ln income Basic	Ln income Heckman corrected
EWM variable		...at 8 y/o	...at 22 y/o	...at 19 y/o	...at 22 y/o	...at 13 y/o	...at 22 y/o	
		Panel A: Only Boys						
In utero	Above p90	0.052	0.149	-0.358	0.021	0.017		-0.055
		(0.047)	(0.290)	(0.612)	(0.029)	(0.028)		(0.127)
	Below p10	-0.045	0.572**	-1.429**	-0.024	-0.061*		0.007
		(0.037)	(0.269)	(0.663)	(0.019)	(0.029)		(0.133)
Infancy	Above p90	0.014	-0.015	-0.372	-0.043***	-0.046***		0.029
		(0.024)	(0.193)	(0.437)	(0.010)	(0.014)		(0.082)
	Below p10	-0.032	-0.318	0.035	0.009	-0.044		0.151
		(0.045)	(0.278)	(0.958)	(0.025)	(0.032)		(0.162)
	R2	*0.120*	*0.123*	*0.248*	*0.120*	*0.220*		
	N	*345*	346	*345*	*346*	*346*		*346*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*		*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*		*YES*
		Panel B: Only Girls						
In utero	Above p90	0.000	-0.511**	0.609	0.000	-0.009	-0.201	
		(0.032)	(0.200)	-1.083	(0.044)	(0.031)	(0.249)	
	Below p10	-0.011	0.063	-0.247	-0.019	-0.043*	-0.021	
		(0.025)	(0.147)	(0.564)	(0.021)	(0.023)	(0.139)	
Infancy	Above p90	0.021	-0.011	0.195	-0.007	-0.032**	-0.005	
		(0.025)	(0.177)	(0.334)	(0.013)	(0.015)	(0.125)	
	Below p10	-0.001	-0.272	-1.148*	-0.008	-0.023	-0.255	
		(0.037)	(0.263)	(0.604)	(0.022)	(0.026)	(0.170)	
	R2	*0.122*	*0.123*	*0.354*	*0.159*	*0.140*	*0.662*	
	N	*364*	360	*356*	*364*	*362*	*161*	
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	

Note: clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table A.2: Early-life temperature EWM effect on mediators and income, by gender

		Dependant variables						
		Total difficulties score	Child height	Child test score	Highest educational level	Dropout & child labour bef. 13 y/o	Ln income Basic	Ln income Heckman corrected
EWM variable		...at 8 y/o	...at 22 y/o	...at 19 y/o	...at 22 y/o	...at 13 y/o	...at 22 y/o	
		Panel A: Only Boys						
In utero	Above p90	0.043	0.571*	-1.095	-0.015	-0.052		0.072
		(0.025)	(0.302)	(0.916)	(0.023)	(0.044)		(0.159)
	Below p10	0.046	0.182	-0.422	0.026	0.050		0.200**
		(0.040)	(0.293)	(0.699)	(0.026)	(0.036)		(0.083)
Infancy	Above p90	0.021	-0.081	-1.811**	-0.009	-0.024		-0.106
		(0.032)	(0.256)	(0.809)	(0.029)	(0.034)		(0.149)
	Below p10	0.004	0.199	-0.874*	-0.020	-0.038*		-0.206***
		(0.022)	(0.136)	(0.456)	(0.014)	(0.020)		(0.076)
	R2	*0.101*	0.123	*0.264*	*0.104*	*0.212*		
	N	345	346	345	346	346		346
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*		*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*		*YES*
		Panel B: Only Girls						
In utero	Above p90	0.032	-0.575*	1.506*	0.029	-0.014	0.184	
		(0.027)	(0.277)	(0.748)	(0.019)	(0.027)	(0.215)	
	Below p10	0.039	-0.470	0.767	0.033	-0.024	0.256	
		(0.030)	(0.294)	(0.598)	(0.021)	(0.024)	(0.229)	
Infancy	Above p90	0.013	-0.166	-1.474**	-0.004	-0.044*	0.043	
		(0.023)	(0.294)	(0.547)	(0.018)	(0.021)	(0.162)	
	Below p10	-0.029	-0.127	-0.770	0.010	0.025*	-0.038	
		(0.020)	(0.231)	(0.489)	(0.015)	(0.012)	(0.139)	
	R2	*0.124*	0.132	*0.355*	*0.168*	*0.148*	*0.660*	
	N	364	360	356	364	362	161	
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	

Note: clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table A.3: In utero rainfall EWM effect on mediators and income, by trimester of gestation

		Dependant variables					
		Total difficulties score	Child height	Child test score	Highest educational level	Dropout & child labour bef. 13 y/o	Ln income Heckman corrected
EWM variable in utero		...at 8 y/o	...at 22 y/o	...at 19 y/o	...at 22 y/o	...at 13 y/o	
Above p90	1 Trim.	0.061	-0.431	0.715	0.031	-0.007	-0.151
		(0.064)	(0.370)	(1.342)	(0.051)	(0.046)	(0.234)
	2. Trim	0.106	0.727	0.669	0.009	0.019	-0.241
		(0.069)	(0.549)	(0.942)	(0.039)	(0.036)	(0.242)
	3. Trim	-0.017	-0.561**	-0.661	-0.066**	-0.031	0.067
		(0.043)	(0.254)	(0.935)	(0.029)	(0.032)	(0.119)
Below p10	1 Trim.	-0.050	0.244	-1.626*	-0.018	-0.063**	-0.032
		(0.033)	(0.291)	(0.794)	(0.033)	(0.029)	(0.222)
	2. Trim	0.006	0.125	-1.159*	-0.009	-0.042	-0.033
		(0.047)	(0.190)	(0.626)	(0.023)	(0.028)	(0.263)
	3. Trim	-0.066	0.376	0.819	-0.054*	-0.020	0.059
		(0.056)	(0.503)	(1.106)	(0.031)	(0.039)	(0.194)
	R2	*0.112*	*0.617*	*0.313*	*0.143*	*0.135*	
	N	*709*	*706*	*701*	*710*	*708*	*710*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table A.4: In utero temperature EWM effect on mediators and income, by trimester of gestation

EWM variable in utero		Total difficulties score ...at 8 y/o	Child height ...at 22 y/o	Child test score ...at 19 y/o	Highest educational level ...at 22 y/o	Dropout & child labour bef. 13 y/o ...at 13 y/o	Ln income Heckman corrected
		Dependant variables					
Above p90	1 Trim.	0.022	0.236	0.336	0.012	0.062	0.209
		(0.043)	(0.441)	(1.645)	(0.058)	(0.062)	(0.269)
	2. Trim	0.016	-0.562	-1.435*	0.011	-0.080**	-0.160
		(0.035)	(0.378)	(0.812)	(0.020)	(0.029)	(0.169)
	3. Trim	0.092***	0.246	-0.431	-0.013	-0.061	0.113
		(0.027)	(0.284)	(1.152)	(0.026)	(0.040)	(0.144)
Below p10	1 Trim.	0.001	0.337	1.317	0.049	0.067	0.269
		(0.050)	(0.319)	(0.808)	(0.030)	(0.040)	(0.170)
	2. Trim	0.036	-0.167	-1.258	-0.010	0.042	-0.013
		(0.033)	(0.370)	(0.887)	(0.029)	(0.034)	(0.214)
	3. Trim	0.039	-0.396	-1.056	0.037*	-0.050*	0.025
		(0.048)	(0.361)	(1.198)	(0.021)	(0.025)	(0.187)
	R2	*0.106*	*0.613*	*0.307*	*0.147*	*0.151*	
	N	*709*	*706*	*701*	*710*	*708*	*710*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table A.5: Early-life monsoon shocks effect on mediators and income

EWM monsoon variable		Total difficulties score ...at 8 y/o	Child height ...at 22 y/o	Child test score ...at 19 y/o	Highest educational level ...at 22 y/o	Dropout & child labour bef. 13 y/o ...at 13 y/o	Ln income Heckman corrected ...at 22 y/o
		Dependant variables					
In-utero	Above p90	-0.032	-0.124	0.930	0.031	0.079	0.081
		(0.053)	(0.719)	(1.564)	(0.051)	(0.048)	(0.198)
	Below p10	-0.030	0.203	0.435	0.009	-0.039	0.155
		(0.035)	(0.276)	(0.841)	(0.039)	(0.034)	(0.152)
Infancy	Above p90	-0.015	-0.177	0.107	-0.066**	-0.105**	-0.021
		(0.044)	(0.443)	(1.251)	(0.029)	(0.039)	(0.215)
	Below p10	-0.059	-0.119	-1.025	-0.018	-0.066	-0.268
		(0.045)	(0.288)	(0.951)	(0.033)	(0.051)	(0.204)
	R2	*0.103*	*0.611*	*0.305*	*0.145*	*0.145*	
	N	*709*	*706*	*701*	*710*	*708*	*710*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

B. Additional definitions of EWM

Table B.1: Step 3 with dummy definition of EWM

EWM dummy variable		Ln income: Heckman corrected ...at 22 y/o					
			Indirect Effect coming from the mediator...				
		Direct Effect	Total difficulties score ...at 8 y/o	Child height ...at 22 y/o	Child test score ...at 19 y/o	Highest educational level ...at 22 y/o	Dropout & child labour bef. 13 y/o ...at 13 y/o
		Panel A: Rainfall EWM					
In utero	Above p90	-0.041	-0,002	-0,002	-0,008	0,015	0,060
	Below p10	-0.204	-0,002	-0,030	-0,002	0,029	-0,038
Infancy	Above p90	-0.785**	-0,002	-0,001	-0,015	-0,024	-0,063
	Below p10	0.745***	-0,001	0,005	-0,002	-0,072	-0,014
	N	*710*	*709*	*710*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
		Panel B: Temperature EWM					
In utero	Above p90	0.489	0,003	0,008	-0,004	-0,055	-0,020
	Below p10	-0.216	-0,001	0,009	-0,001	-0,115	0,118**
Infancy	Above p90	-0.443	0,003	0,007	0,006	-0,014	-0,011
	Below p10	-0.070	0,002	0,001	-0,034	-0,114	0,114
	N	*708*	*709*	*710*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table B.2: Step 3 with 80/20 criteria

EWM variable		Direct Effect	Total difficulties score ...at 8 y/o	Child height ...at 22 y/o	Child test score ...at 19 y/o	Highest educational level ...at 22 y/o	Dropout & child labour bef. 13 y/o ...at 13 y/o
			Ln income: Heckman corrected ...at 22 y/o — Indirect Effects coming from the mediator...				
			Panel A: Rainfall EWM				
In utero	Above p80	-0.067	0,002	0,001	0,000	-0,026	0,013
	Below p20	0.039	-0,001	-0,004	0,004	0,014	-0,032***
Infancy	Above p80	0.032	0,001	0,001	0,000	0,020***	-0,017*
	Below p20	0.001	-0,000	0,004	0,001	-0,006	-0,013
	N	*710*	*709*	*710*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
			Panel B: Temperature EWM				
In utero	Above p80	0.149	0,001	0,002	-0,000	-0,003	-0,018
	Below p20	0.196*	0,001	0,005	0,000	-0,020	0,002
Infancy	Above p80	-0.115	0,001	-0,000	0,002	-0,003	-0,006
	Below p20	-0.127*	-0,000	-0,002	0,001	-0,002	0,004
	N	*710*	*709*	*710*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table B.3: Step 3 with 95/05 criteria

EWM variable		Direct Effect	Total difficulties score ...at 8 y/o	Child height ...at 22 y/o	Child test score ...at 19 y/o	Highest educational level ...at 22 y/o	Dropout & child labour bef. 13 y/o ...at 13 y/o
			Ln income: Heckman corrected ...at 22 y/o — Effect coming from the mediator...				
			Panel A: Rainfall EWM				
In utero	Above p95	-0.109	0,002	0,008	-0,000	-0,012	-0,006
	Below p05	-0.001	-0,002	-0,004	0,004	0,016	-0,035**
Infancy	Above p95	0.007	0,001	0,001	-0,000	0,030***	-0,022**
	Below p05	-0.009	-0,001	0,004	0,001	0,008	-0,017
	N	*710*	*709*	*706*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
			Panel B: Temperature EWM				
In utero	Above p95	0.016	0,002	-0,001	-0,000	-0,025	0,005
	Below p05	0.176*	0,001	0,003	0,000	-0,012	0,004
Infancy	Above p95	-0.102	0,001	0,006	0,005	0,009	-0,021
	Below p05	-0.119	-0,000	0,000	0,002	-0,002	0,003
	N	*710*	*709*	*706*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

C. Alternative *lntotinc* threshold

Table C.1: Step 3 with alternative threshold for lntotinc

EWM variable		Direct Effect	Total difficulties score ...at 8 y/o	Child height ...at 22 y/o	Child test score ...at 19 y/o	Highest educational level ...at 22 y/o	Dropout & child labour bef. 13 y/o ...at 13 y/o
		Ln income: Heckman corrected ...at 22 y/o	Indirect Effect coming from the mediator...				
		Panel A: Rainfall Shocks					
In utero	Above p90	-0,093	0,002	-0,000	0,000	-0,007	0,001
	Below p10	0,032	-0,001	0,000	-0,001	0,012	-0,005
Infancy	Above p90	0,042	0,001	-0,000	-0,000	0,015**	-0,004
	Below p10	0,053	-0,001	-0,003	-0,001	-0,000	-0,003
	N	*710*	*709*	*706*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
		Panel B: Temperature Shocks					
In utero	Above p90	0,014	0,001	-0,000	0,000	-0,004	-0,002
	Below p10	0,024	0,001	-0,000	0,000	-0,012	0,001
Infancy	Above p90	-0,012	0,001	-0,000	-0,002	0,003	-0,002
	Below p10	-0,019	-0,000	0,000	-0,001	0,001	-0,000
	N	*710*	*709*	*706*	*701*	*710*	*708*
	Wealth FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
	Regional FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Clustered standard errors by YL cluster in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.