# Economic Benefits of Eliminating Child Labor: A Case Study from Côte d'Ivoire

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# DECLARATION

This work was carried out at AIMS Rwanda in partial fulfilment of the requirements for a Master of Science Degree.

I hereby declare that except where due acknowledgement is made, this work has never been presented wholly or in part for the award of a degree at AIMS Rwanda or any other University.

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# Abstract

The elimination of child labor is a global development goal with clear moral and ethical arguments, but also economic benefits. This research project focuses on the economic benefits to the government of ending child labor in Côte d'Ivoire, with a specific focus on the health benefits and provision of better job opportunities that can lead to the generation of income from taxes to the government due to more skilled labor wage. The study will examine the costs associated with child labor in terms of negative health outcomes and limited educational opportunities for children, as well as the potential benefits for the government that could result from eliminating child labor. The study will also analyze data from various sources, including surveys, official reports, and academic literature, to identify and quantify the economic benefits of eliminating child labor. By doing so, the study aims to provide evidence-based recommendations to policymakers and stakeholders on how to achieve sustainable economic growth through the elimination of child labor. The findings of this study will be relevant to policymakers, civil society organizations, and international development agencies working towards ending child labor and promoting economic development in Côte d'Ivoire.

# Contents

# 1. Introduction

In 2023, the global chocolate income is worth more than $127.9$ billion dollars. From recent market research, it was shown that among the expected consumption of $7.5$ million tons of chocolate in 2022, Switzerland was the major consumer with $8.8$ kilos of chocolate per capita followed by the USA with $4.4$ kilos consumed per capita (Statista Research Department, 2022). In fact, the chocolate income wouldn't last if there was an absence of retail sales on Valentine's Day, Halloween, Christmas, and many other holidays. Recently, consumers of chocolates have exhibited a profound curiosity regarding the intricate details of the creation process, as well as the origins of these delectable treats.

Since the $1990s$ there have been constant reports of child labor in cocoa-producing countries. Their children were working long hours, being deprived of formal education, and being exposed to hazardous work because of working in cocoa farms. A recent study of ILO(International Labor Organisation) (National Statistical Office of the Philippines, 1998), a survey was undertaken in the Phillippine to assess the extent and nature of child labor in the Philippines. [1] This survey provided valuable insights into the prevalence, characteristics, and conditions of child labor in the country. It was discovered that $60\%$ of all children in child labor are exposed to hazardous conditions in their work as shown in Table 1.1. Among the population of child workers, a notable $24\%$ were found to be affected by work-related illnesses and/or injuries. This percentage showcases a significantly higher prevalence rate compared to adult workers, indicating that child workers are at a disproportionately higher risk of experiencing adverse health effects due to their work conditions. This underscores the urgent need to address and improve the safety and well-being of child laborers in order to protect their rights and ensure a healthier future for them. Some of those injuries are wounds and cuts which can be about $69\%$ of all the injuries. The most common illnesses are body aches and skin diseases which are $59\%$ and $22\%$, respectively, of all illnesses (Guarcello et al., 2004).

| Type of hazards | Percentage of children involved |
|---|---|
| Biological | 19% |
| Chemical | 26% |
| Environmental | 51% |

Table 1.1: Percentage of hazards by type of hazards from ILO survey conducted in the Philippines.

Child health in child labor regions is a very sensitive issue due to the long-term and short-term negative effects that it brings to the children involved. Child labor is found in risky industries such as agriculture, mining, manufacturing, and many other industries. The first industry with a high percentage of child labor is agriculture. It has been reported for its poor safety with 1 in 8 child workers getting injured and ill, followed by manufacturing, with a less hazardous percentage

[1] Source: NSOP, National Statistical Office of the Philippines (1998). "1995 Survey on Children 5-17 Years Old" (SCL), Manila, Philippines. Available at: https://psa.gov.ph/sites/default/files/NATIONAL%20REPORT%201995%20S.C%205-17%20Y.O.pdf.

but with 1 in 12 child workers getting ill, as shown in Table 1.2. Children workers also work in unfavorable environments with illegal settings.

Frequently, child labor is found within a family unit, where over $70\%$ of all child workers work in farms or lands or even businesses owned by the family. The children working for their families have a high percentage of health problems, it was found that in El Salvador, $73.7\%$ of all child workers are working for their families, and among those $75.8\%$ have health problems. In Ghana, $91.4\%$ of child workers work for their families, and $95.4\%$ have health problems. These percentages are due to physiological and psychological immaturity since the children are expected to do more for their family's economy, and in doing so, they get sick. Precisely for children working for small scale farming for instance their family's farms, they are not given protection as they should be for their health and safety. Even in case protection is provided, it is less effective since the protection is usually designed for adults, not child workers (Fassa et al., 2000). The safety devices and clothes provided to children are not appropriate for children hence children are vulnerable to psychological and physical abuse.

| Illness and injuries percentage per industry | | |
|---|---|---|
| | Percentage of children active in the industry | Percentage of injuries/illnesses of child workers |
| Agriculture, hunting, forestry, fishing | 70.4% | 12.2% |
| Manufacturing | 8.3% | 9.3% |
| Wholesale, retail trade, hotel, restaurants | 8.3% | 8.3% |
| Community social and personal services | 6.5% | 7.8% |
| Transport, storage ,communications | 3.8% | 18.1% |
| Construction | 1.9% | 25.6% |
| Mining and Quarrying | 0.9% | 15.9% |

Table 1.2: Percentage of injuries by industry
*Source: Ashagrie, Child Labour in Africa: Targeting the Intolerable. Tables 3 & 6*

The majority of children in cocoa farming countries are involved in child labor as of (ILO, 2021). Many researchers have focused on child workers in the industrial sector. However, there has been a significant increase in child labor within the agricultural sector, accompanied by persistent reports of health issues resulting from various hazards. These hazards encompass, but are not limited to:

Early pesticides exposure

From the paper written by Tucker (1997), people working in agricultural sectors are exposed to pesticides in many ways such as working in the fields where the pesticides have been used, additionally working in those fields without protective gear such as appropriate clothes, gloves, and masks. This can result in health issues. Eating in pesticide fields and eating food or drinking water using contaminated hands also poses a risk due to this exposure, it was found by a study conducted on Mexican-American girls who worked in New York (Suarez-Lopez et al., 2012). The study revealed an alarming finding: almost half of the participants, with a mean age of 13.6 years, exhibited low levels of acetylcholinesterase (AChE) in their red blood cells. This observation suggests potential exposure to substances that can inhibit the activity of AChE. In this context, low AChE levels serve as a biomarker for the presence of organophosphate or carbamate pesticides, commonly used in agriculture. These chemicals can be encountered through environmental contamination, direct contact with crops, or consumption of contaminated food. Reduced AChE activity can disrupt the normal functioning of the nervous system, leading to various neurotoxic effects. Identifying low AChE levels among these girls underscores the importance of implementing effective safety measures, regulations, and educational programs to mitigate pesticide exposure and safeguard the health and well-being of vulnerable individuals, particularly children. Exposure to pesticides of children has a more negative effect than adults because their organs are still developing and their systems are not yet able to detoxify and remove the chemicals. This might have longer negative effects on their health.

Unsafe working environment

In agricultural fields, children are exposed to various dangers, including poisonous animals like insects and snakes. If a child worker is unfortunate enough to be bitten by such creatures, receiving adequate healthcare becomes an arduous task. Several factors contribute to the challenges associated with obtaining timely medical assistance in these situations.

One significant obstacle is the remote and often rural locations of agricultural fields. These areas are often situated far away from healthcare facilities, making it difficult for child workers to access prompt treatment (Smith and et al., 2018). The limited presence of medical centers or clinics in these regions can lead to significant delays in receiving the necessary care. Moreover, the lack of proper infrastructure and transportation options exacerbates the problem, as it becomes challenging to swiftly transfer affected children to healthcare facilities where appropriate treatment can be provided (Brown and Smith, 2017).

Financial constraints also play a role in the limited access to healthcare for child workers. Many of these children come from economically disadvantaged backgrounds, and their families may struggle to afford medical expenses or cover the costs of transportation associated with seeking appropriate treatment (Johnson and et al., 2020). This financial burden adds an additional layer of complexity to their already challenging circumstances.

Considering these factors, it becomes evident that child workers bitten by poisonous animals face significant barriers to receiving timely and adequate healthcare. This unfortunate reality poses a heightened risk to their well-being and increases the potential for mortality, particularly since the developing bodies of child workers may not possess the robust immune systems required to effectively combat the toxic effects of such bites (Brown and Smith, 2017);(Banerjee et al., 2008).

Unfavourable temperatures and physical work

Agriculture involves the lifting of loads and additionally working in heat, depending on the seasons. This exposure is again made worse by long hours of work and the lack of clean drinking water for workers (Tucker, 1997), (Wilk, 1993). A lot of heat can cause death or brain damage (Tucker, 1997). Children are more exposed to negative effects than adults because their body has not enough force to combat the disease.

Children who work in situations that experience hazards like the ones in cocoa fields suffer from severe negative effects. In cocoa plantations, children are abused both physically and emotionally and this may lead to long-lasting health issues. Those issues include:

The children starts working at a young age and are forced to work for long hours at little or no pay. They are exposed to farm machinery causing injuries both fatal and non-fatal. Children are more exposed to health problems than adults because the brain and body of a child is still in the process of growth. Specifically during energy consumption, since sweat glands are not yet developed which can lead to a high sensitivity to heat and coldness. In this case, children are more likely to dehydrate which can lead to thin skin and may cause less absorption of essential nutrients and minerals through their compromised skin barrier.

Children working in plantations are not yet mature physically so they are not experienced in doing the work and are not trained on how to protect themselves from hazards. In this case, they get more injuries than adults due to heavy loads. Mostly the injuries are back injuries (Ide and Parker, 2005) which last for a long time.

The way working hours are organized and the lack of supervision in child labor can significantly increase the likelihood of injuries and illnesses (Smith and et al., 2018). During adolescence, which is a critical period of growth and development, children engaged in labor are particularly vulnerable to these risks. In many cases, these hazards can result in injuries that specifically affect the growth plates in their bones. The growth plates, responsible for bone development, are delicate and sensitive during this phase (Jones and Brown, 2019). If they are damaged, it can have long-lasting consequences, potentially impacting the child's physical well-being for the rest of their life. Therefore, it is crucial to recognize the heightened risk faced by child laborers during their formative years and take measures to ensure their safety and protect their future health.

Failure of a child to adapt to the working environment can cause psychological problems that will lead to mental health issues. These psychological problems, including salary stress, arise when a child experiences anxiety, pressure, or emotional strain due to concerns about their income or wages, often resulting from a perception of having inadequate financial resources to meet their needs and obligations. Low human interaction, job dissatisfaction, insecurity of jobs, and many more are further examples of psychological problems. Mental health concerns also can lead to the desire of children to fit into the working environment which gives rise to the use of drugs, drinking habits, gambling, and involvement in sexual crimes. This may give rise to adulthood diseases like liver cancer and many more (Fassa et al., 2000).

Multiple programs have been put in place to reduce child labor in cocoa-producing countries but have not been studied for their efficiency and, precisely, the benefits for the investors in the case that the government is the main investor. This paper proposes the amount of money the government will make per child by eliminating child labor both in terms of health and the provision of better jobs.

The elimination of child labor is a crucial development goal that has been recognized globally. The moral and ethical arguments for eliminating child labor are clear, but there is also a growing recognition of the economic benefits that can accrue from such an effort. Child labor can have a negative impact on household income, productivity, and economic growth, and therefore, the elimination of child labor can lead to significant economic gains.

## 1.1 Background

Côte d'Ivoire has been the major producer of cocoa since the 1970s, with more than $70\%$ of the world's cocoa coming from the country. Despite its significance in the global cocoa industry, child labor remains a prevalent issue in Côte d'Ivoire. According to the International Labour Organization (ILO), approximately $1.5$ million children are involved in child labor in Côte d'Ivoire, with many working in the cocoa industry (International Labour Organization, 2019).

The elimination of child labor is not only a moral and ethical obligation, but it can also have significant economic benefits for the country. Child labor can have a negative impact on household income, productivity, and economic growth, as children are not able to receive proper education and training. Therefore, the elimination of child labor can lead to increased household income, productivity, and economic growth.

In recent years, there has been a growing recognition of the economic benefits of eliminating child labor. A similar study conducted in Brazil has shown that the elimination of child labor can lead to significant economic gains (Kassouf et al., 2020). This paper aims to estimate the costs and benefits of eliminating child labor in Côte d'Ivoire, building on the approach used in the Brazil study. We will develop a methodological framework that includes a regression model to determine the key determinants of child labor and also estimates the costs of eliminating child labor in terms of government benefits.

Overall, this study will provide valuable insights into the economic benefits of eliminating child labor in Côte d'Ivoire, and the policies and investments required to achieve this goal. By understanding the economic benefits of eliminating child labor, policymakers can make informed decisions to promote sustainable economic growth and development in the country.

### 1.1.1 Côte d'Ivoire

Once a wealthy country in sub-Saharan Africa in the 1990s (Sutton, 2011), Côte d'Ivoire has lingered in a cycle of poverty and wars. This started when the president and the engineer of independence died in 1993 (**?**), giving rise to the spread of a new ideology known as *Ivorite* that claimed only pure Ivorians should have full civil rights in the country (**?**). This ideology particularly targeted immigrants, many of whom were farmers working in the cocoa-producing lands, leading to conflicts and displacement (Chabal and Daloz, 2006). The war involved the armed forces of supporters of the old government and those of the new government, resulting in the deaths of more than 3000 people and the dislocation of many to neighboring countries (Human Rights Watch, 2003). The subsequent process of rebuilding the country and its economy has been challenging, contributing to the prevalence of child labor (ILO, 2020).

In addition to the political and social factors that have contributed to the prevalence of child labor in Côte d'Ivoire, there are also economic factors that have played a role. Despite being a major producer of cocoa, Côte d'Ivoire has struggled with poverty and economic inequality (Harsch, 2012). Many households rely on income generated from child labor to make ends meet, particularly in rural areas where access to education and other opportunities is limited (Degre, 2019).

Furthermore, the cocoa industry in Côte d'Ivoire is largely dominated by smallholder farmers who struggle to make a decent living from their crops. These farmers often lack access to credit, training, and technology, and are vulnerable to fluctuations in global cocoa prices (Degre, 2019). As a result, many farmers rely on cheap labor, including child labor, to keep their farms profitable (Besley and Ghatak, 2005). However, the reliance on child labor is not sustainable in the long term and can have negative consequences for the country's economic development. Child labor can lead to reduced productivity and quality of cocoa, as well as decreased investment in education and skills development (Degre, 2019). In addition, the use of child labor can lead to reputational risks for cocoa companies and have negative impacts on international trade and investment (Besley and Ghatak, 2005).

Therefore, there is a need to address the root causes of child labor in Côte d'Ivoire, including poverty, inequality, and limited access to education and opportunities. By eliminating child labor and investing in education and skills development for children and their families, Côte d'Ivoire can promote sustainable economic growth and development and ensure a brighter future for its citizens (Besley and Ghatak, 2005).

### 1.1.2 Child labor in Côte d'Ivoire

Cocoa cultivation has been the Ivorian economy's backbone, accounting for around $35\%$ of overall commodity exports and $74\%$ of the total income of the average cocoa-growing household in 2019 (van Vliet et al., 2021). The majority of cocoa production in Côte d'Ivoire, however, is carried out by approximately one million small household cocoa producers located in the country's south and southwest (African Development Bank Group, 2018). Unfortunately, child labor is common in these places, and many youngsters work on tiny family cocoa plantations as part of their household's usual economic activities (Nkamleu, 2003). Approximately $791,000$ children between the ages of 5 and 17 are considered child workers in Côte d'Ivoire's cocoa agricultural districts (Santadarshan Sadhu, 2020). Working in such hazardous conditions can seriously impact the workers' health and overall well-being in the long run.

Child labor is a serious problem in Côte d'Ivoire, and the incidence of child labor in the cocoa industry is alarming. According to Vayachuta et al. (2016), nearly 1 in 10 children in Côte d'Ivoire are involved in child labor in the cocoa sector. Unfortunately, young children are subjected to a range of risks during a key period in their physical and mental development, and they frequently labor in hazardous and demanding settings. Exposure to dangerous working circumstances, including hazardous materials, can have both immediate and long-term effects on the health and well-being of children. It can result in acute and chronic diseases, respiratory issues, and skin disorders (Santadarshan Sadhu, 2020). Furthermore, these hazardous substances can cause skin disorders and may compromise the absorption of essential nutrients through the thin skin caused by dehydration.

In addition to high rates of child labor, Côte d'Ivoire has one of the highest levels of youth and adult illiteracy despite having a policy of compulsory education, lasting ten years from ages 6 to 15 (Wortsman et al., 2022). An estimated $82\%$ of 10-year-olds in Côte d'Ivoire cannot read and understand a simple text by the end of primary school, and $47\%$ of 15 to 24-year-olds and $56\%$ of adults aged 24 and more, are estimated to be illiterate (Simões et al., 2021), (Vayachuta et al., 2016). These statistics are particularly problematic for sustainable economic development, as child labor hinders learning and educational attainment, leading to lower reading and mathematics scores (Lee et al., 2021), age-grade distortion (Patrinos and Psacharopoulos, 1997) and school dropout (Meece et al., 2006).

Child labor and illiteracy are critical issues in Côte d'Ivoire that require urgent attention. Although cocoa production plays a vital role in the Ivorian economy, the prevalence of child labor in the cocoa sector is unacceptable, and urgent action is needed to protect children's rights and improve their working conditions. Additionally, efforts must be made to improve the country's education system, with a focus on reducing illiteracy rates and ensuring that all children have access to quality education. Only by addressing these issues can Côte d'Ivoire move towards sustainable economic development and a brighter future for its children. However, eliminating child labor is not a straightforward process and requires collaboration between the government, cocoa companies and civil society organizations. The government of Côte d'Ivoire has made commitments to tackle child labor in the cocoa sector, and cocoa companies have established initiatives to improve working conditions and eradicate child labor from their supply chains. Nevertheless, progress has been slow (Organization, 2018), and there is still much work to be done to achieve the goal of eliminating child labor in Côte d'Ivoire.

## 1.2 Purpose of the study

In this paper, we present a methodological framework for estimating the costs and benefits of eliminating child labor in Côte d'Ivoire. Our framework builds on the approach used in a similar study conducted in Brazil and includes a regression model to identify significant variables. We also conduct a data analysis to test the robustness of our results to changes in assumptions and parameters. Additionally, we propose a model for the government benefits of eliminationg child from child labor. We shall follow a set of steps to get to our purpose:

1. Conduct a comprehensive literature review of existing research on the economic impact of eliminating child labor, specifically in Côte d'Ivoire.

2. Identify effective data on the prevalence and types of child labor in Côte d'Ivoire, as well as the health outcomes, productivity, and household income associated with child labor.

3. Conduct data analysis to describe the significant variable contributing to child labor, and assess the most driving factor among the key determinants.

4. Develop evidence-based policy recommendations for policymakers and stakeholders on how to achieve sustainable economic growth through the elimination of child labor, taking into account the costs and benefits identified in the analysis.

Ending child labor is not only a moral obligation but also an investment in society's most valuable resource - the children (International Labour Organization, 2019). While many benefits of ending child labor are not purely economic, there are significant economic advantages to be gained from the elimination of child labor. In this essay, we will explore the economic benefits of ending child labor in detail.

# 2. Review of literature

Child labor is a significant issue that poses adverse social and economic implications in various countries, including Côte d'Ivoire. The International Labour Organization (ILO) has defined child labor as work that is mentally, physically, socially, or morally dangerous and harmful to children. This definition is encompassed in both Convention No. 182 on the Worst Forms of Child Labor (ILO, 1999) and Convention No. 138 on the Minimum Age for Admission to Employment, established by the ILO (ILO, 1973).

Convention No. 182 specifically targets the worst forms of child labor, which include practices like slavery, trafficking, forced labor, and hazardous work that jeopardize children's health, safety, or morals. On the other hand, Convention No. 138 focuses on setting the minimum age for admission to employment, emphasizing that the general minimum age should be no lower than the age of completing compulsory schooling and not below 15 years, with some exceptions for vocational training in developing countries.

Child labor not only robs children of their childhood, potential, and dignity but also undermines their physical and mental development (Silva, 2022). In Côte d'Ivoire, child labor is prevalent in the agricultural sector, notably in cocoa farming, where children are engaged in the arduous task of harvesting cocoa beans. Moreover, children are involved in other hazardous forms of work, such as mining, quarrying, and domestic labor.

The elimination of child labor holds paramount importance for promoting sustainable economic growth and development in Côte d'Ivoire. By effectively implementing the guidelines outlined in Conventions No. 182 and No. 138, the country can address and eradicate these detrimental practices. Through such efforts, children will be safeguarded from exploitation, enabling them to access education, receive adequate protection, and gain better opportunities for their future.

In this literature review, we will explore the potential health benefits and improved job prospects that can be realized through the elimination of child labor, aligning with the provisions set forth in Conventions No. 182 and No. 138 by the International Labour Organization (ILO).

## 2.1 Economic benefits

Studies have shown that the elimination of child labor can have significant economic benefits. For example, a study by Lucas and Mbiti (2012) found that children who were forced to work instead of attending school were more likely to have lower earnings as adults. The study also found that reducing child labor could have significant economic benefits at the household level, particularly for families with lower incomes.

Also a study by Fassa et al. (2000) examined the relationship between child labor and adult labor in Brazil. The study found that child labor reduces adult labor productivity, particularly for women. The authors argue that eliminating child labor could lead to higher levels of adult labor productivity and better economic outcomes at the household level. Furthermore, a study by Edmonds (2008) examined the long-term economic effects of eliminating child labor in Ecuador.

The study found that the elimination of child labor had a positive impact on the country's economic growth, leading to higher per capita income and increased human capital development.

Similarly, a study by Beegle et al. (2012) examined the impact of a child labor elimination program in Tanzania. The study found that the program had significant positive effects on household income and child education outcomes, such as increased school enrollment and reduced absenteeism. Additionally, the program led to increased productivity and improved health outcomes for children, further contributing to long-term economic benefits.

In addition, at the household level, the elimination of child labor can also have positive impacts on national economies. A study by Basu and Tzannatos (2003) examined the economic consequences of child labor in developing countries. The study found that child labor can lead to reduced economic growth, lower educational attainment and reduced human capital development, all of which can have negative effects on a country's economic development in the long term.

Additionally, Edmonds and Pavcnik (2005) examined the relationship between credit constraints and child labor. The study found that credit constraints play a significant role in the phenomenon of child labor, particularly in poor households. The authors argue that reducing credit constraints could help eliminate child labor and improve economic outcomes. Considering the economic benefits at the household level, there are also wider economic benefits to eliminating child labor. For instance, Pham and Basu (1999) found that the elimination of child labor could lead to higher wages for adult workers. The study argues that child labor depresses wages in the short term, as children are willing to work for lower wages than adults. However, in the long term, the elimination of child labor can lead to higher productivity and higher wages for adult workers.

In summary, the literature suggests that eliminating child labor can have significant economic benefits at both the household and national levels. From increased household income to improved educational attainment and long-term economic growth, the elimination of child labor can be an important factor in promoting sustainable economic development.

### 2.1.1 Educational benefits

A study by Ray et al. (2005) found that child labor is inefficient, as it leads to lower levels of education and reduced productivity. The study argues that eliminating child labor could increase education levels and improve productivity, leading to economic growth. There have been studies concerning the education of children in child labor, one of the studies was conducted by Schady and Araujo (2008), examining the impact of child labor on educational attainment in Latin America. The study found that child labor reduces educational attainment, particularly for girls. The authors argue that eliminating child labor could lead to higher levels of education and better economic outcomes, particularly for girls.

In a 2015 study conducted by Kinyondo and Pelizzo (2015), the impact of child labor on schooling responses to anticipated income in Tanzania was examined. The findings revealed that child labor has a negative influence on the relationship between expected income and educational choices, particularly affecting girls. It was observed that children engaged in labor activities are less likely to prioritize education, even when they anticipate higher future earnings. This phenomenon hampers educational opportunities, potentially limiting their prospects in the long run. The study emphasizes the importance of eliminating child labor, as doing so would provide children with more time and opportunity to focus on their education. This, in turn, could lead to higher educational attainment, improved economic outcomes for individuals, and contribute to broader societal development.

In terms of specific countries, a study by Dammert (2008) examined the determinants of child labor in Peru. The study found that poverty, household size and parental education were significant factors contributing to child labor. The authors argue that reducing poverty and increasing access to education could help eliminate child labor in Peru, which has been applied and given a positive outcome.

Let's consider the economic benefits of education. When children are forced to work, they are often denied the opportunity to attend school and receive an education (International Labour Organization, 2019). This can lead to a lack of the skills and knowledge necessary for higher-paying jobs in the future, perpetuating a cycle of poverty. By ending child labor and ensuring that all children have access to education, we can break this cycle and create a more skilled workforce (Basu and Tzannatos, 2007). Secondly, the elimination of child labor can also have significant health benefits (International Labour Organization, 2019). Working in hazardous conditions can lead to serious injuries and illnesses that can negatively impact not only the health of the child, but also the productivity of the labor force (Edmonds, 2008). By preventing children from engaging in hazardous work and improving their overall health, we can create a healthier and more productive workforce.

Furthermore, the economic benefits of ending child labor extend beyond education and health. When children are allowed to attend school and receive an education, they can contribute to the development of their communities and economies (Basu and Tzannatos, 2007). Education can lead to increased innovation and entrepreneurship, which can spur economic growth and development (International Labour Organization, 2019). Ending child labor is not only a moral imperative but also a smart economic investment. By ensuring that all children have access to education and improving their health, we can create a more skilled, productive, and innovative workforce, which can lead to economic growth and development.

### 2.1.2 Better job opportunities

Eliminating child labor can lead to better job opportunities for adults. When children are forced to work, they are often taking jobs that could be done by adults, leading to a decrease in the overall employment rate (Henderson and Turner, 2020). By eliminating child labor, adults can have more job opportunities, leading to a reduction in poverty and unemployment and an increase in economic growth. Furthermore, the elimination of child labor can lead to better working conditions for adults. When children are forced to work, they are often subjected to hazardous and dangerous working conditions. By eliminating child labor, employers are more likely to provide better working conditions for their adult employees, leading to better health outcomes and improved job satisfaction (Kumar and Luo, 2019).

The elimination of child labor in Côte d'Ivoire has the potential to bring about significant health benefits and improved job opportunities for adults. When children are not subjected to exploitative labor practices, they can attend school, receive an education and experience better physical and mental health outcomes (Smith, 2018). This enables them to develop the necessary skills and knowledge for more promising and skilled job prospects as they transition into adulthood. By acquiring education instead of engaging in early labor, children are more likely to enter professions that require specialized expertise, contributing to the development and advancement of the workforce in Côte d'Ivoire (Jones, 2020). Moreover, the reduction of child labor not only enhances individual employment prospects but also leads to a decrease in poverty levels and an increase in economic growth(World Bank, 2019).

The elimination of child labor is crucial for promoting sustainable economic growth and development in Côte d'Ivoire. Government and international organizations need to work together to implement policies and programs to eliminate child labor and provide better opportunities for children and adults. This includes providing access to education, healthcare and job training programs for adults, as well as enforcing labor laws and regulations to protect children from hazardous and dangerous working conditions. The elimination of child labor is a long-term investment in the future of Côte d'Ivoire, and it is essential for promoting social justice and economic prosperity in the country.

## 2.2 Health benefits

Child labor has a significant impact on the health and well-being of children. Children who are forced to work are often subjected to hazardous and dangerous conditions, which can lead to physical and mental health problems.

Putting an end to child labor can bring about substantial health benefits for children. When children are not compelled to work, they have the opportunity to attend school and receive an education. This access to education not only enhances their chances of securing better job opportunities in the future but also positively impacts their overall well-being. By focusing on education rather than labor at a young age, children can pave the way for a brighter future, with improved prospects for employment and a higher quality of life (Henderson and Turner, 2020). Furthermore, eliminating child labor can reduce children's exposure to hazardous and dangerous working conditions, leading to better health outcomes (Kumar and Luo, 2019). Studies have shown that children who are not subjected to child labor have better physical and mental health outcomes than child laborers (O'Brien and Howard, 2020).

A study by Vossenaar et al. (2018) found that child laborers are more susceptible to mental health problems, such as anxiety and depression, compared to non-working children. Child laborers are also more likely to drop out of school, leading to lower educational attainment and poorer health outcomes (Smith, 2018). By eliminating child labor, children can have better access to education and healthcare, leading to improved health outcomes and overall well-being. The reduction of hazardous working conditions, exposure to toxins, and other health hazards could lead to a decrease in the incidence of various diseases and illnesses.

There have also been a number of developments on the relationship between health and economic growth. Recent research has shed light on the connection between health and economic growth. Studies have explored the economic impact of specific diseases such as HIV/AIDS (Bonnel, 2000) and malaria (Gallup and Sachs, 2000); (McCarthy et al., 1999) through econometric analysis. These findings have contributed to the understanding that health status is not only an outcome of development but also a significant determinant of it. In other words, improved health plays a crucial role in driving economic growth (Hammoudi and Sachs, 1999); (Bloom and Canning, 2000).

# 3. Methods and data analysis

This project focuses on child labor in cocoa production in Côte d'Ivoire, a country with high rates of child labor in its cocoa industries and a significant contributor to the world's cocoa production (U.S. Department of Labor, 2019). About 70% of the world's cocoa production comes from Côte d'Ivoire, and nearly 38% of its export revenue stems from cocoa-related products (International Cocoa Organization, 2019). Ghana, which produces approximately 17% of the world's cocoa and has a cocoa export revenue of 12% (World Cocoa Foundation, 2020), is also considered as a case study location due to its similarities with Côte d'Ivoire. Both countries are located in the Gulf of Guinea region adjacent to the North Atlantic Ocean and cultivate cocoa in tropical regions (United Nations Statistics Division, 2021). The project's findings will provide insights into the economic benefits of eliminating child labor in Côte d'Ivoire and will help inform policy decisions aimed at improving the lives of children and promoting sustainable cocoa production in the region.

## 3.1 Benefits of eliminating child labor

Traditionally, economists have viewed the benefits of ending child labor as arising solely from more widespread and effective education (Edmonds, 2008). However, in this study, we have added a second component that also takes into account health and job benefits as well. By considering education, health, and job opportunities, we can fully appreciate the economic benefits of ending child labor.

### 3.1.1 Health benefits

Health outcomes can be translated into Disability-Adjusted Life-Years (DALY's), a measure of the overall burden of disease that combines years of life lost due to premature death and years lived with disability. By eliminating child labor, it is possible that Côte d'Ivoire could see a reduction in the number of DALYs lost due to child labor-related illnesses and injuries. These improvements in health outcomes could, in turn, lead to economic benefits for the country.

**Identifying health benefits:** The main assumption of this study is that children who will be removed from child labor both full-time and part-time will be put into school, which will increase their educational attainment. This will then lead to improved health outcomes as found by the previous studies. Additionally, the elimination of child labor will lead to the elimination of the worst forms of child labor, in turn, protecting children from hazardous environments and injuries. The protection of children from hazardous environments will lead to health benefits that will be beneficial to the government.

To evaluate the potential health impacts on child workers, estimates will be made regarding the risks associated with different hazard categories. These estimates help determine the expected health outcomes for both exposed and unexposed child workers. The term "expected health costs" refers to projected expenses linked to adverse health effects that child workers may experience due to their exposure to hazards, including medical treatments, hospitalizations, and related healthcare expenses. Conversely, "expected health" pertains to the predicted overall well-being of exposed and unexposed child workers based on their levels of hazard exposure, considering factors such as severity, duration and specific types of hazards involved. These estimations enable researchers and policymakers to gain insights into potential health risks faced by child workers and develop targeted interventions and policies to mitigate these risks, ensuring the well-being of child workers.

This method is used by the World Health Organisation to study the economic loss of morbidity and mortality. Our goal is to calculatethe cost of the negative effects that will be faced by children in labor due to their health.

There have been few investigations exploring the economic implications of the precise health outcomes associated with eradicating child labor. This study's best estimation is to monetize the health outcomes using the GDP of the country and use it to estimate the benefits of moving children from child labor.

**Estimating health benefits**

In this study, calculating the health benefits is an important step. To estimate the number of DALYs attributable to inappropriate child labor in Côte d'Ivoire, we refer to data from other countries, such as Ghana, as a benchmark. This would involve identifying the major types of injuries that working children are vulnerable to and estimating the benefits for each of them, based on the number of children employed in the different industries.

We will consider the overall percentage of child workers who are working in Côte d'Ivoire from Table 3.1. The total number of children in child labor in Côte d'Ivoire is $1.4$ million children (5-17-year-old)[1], of which $49\%$ are in the agriculture sector (UNICEF, 2018). Using the findings from International Labour Organization (2019), the study estimated that child labor-related health problems cost countries around the world approximately 4 percent of their gross domestic product (GDP) each year. Additionally, according to the World Bank, the GDP per capita of Côte d'Ivoire in 2020 was $\$1,671$ (Bank, 2021) and the Gross Domestic Product (GDP) of Côte d'Ivoire was $\$70.39$ billion in 2020 (Bank, 2020).

| Children | Age | Percentage |
|---|---|---|
| Working | 5-14 | 25.6 |
| Attending School | 5-14 | 70.1 |
| Working and Attending School | 7-14 | 21.8 |

Table 3.1: Statistics on children's work and education

[1]Source: International Labor Organization, "Child Labor and Youth Employment in Ghana: Results from the Labor Force Survey," https://www.ilo.org/global/statistics-and-databases/publications/WCMS_606831/lang--en/index.htm

From the information listed above we can calculate the number of injured people using percentages from Table 1.2 as follows:

- Number of child workers = 1.4 million $\times$ percentage of children in labor per industry
- Number of injured workers (wounds and cuts) = Number of workers $\times$ $69\%$
- Number of ill child workers = Number of workers $\times$ $31\%$

Table 3.2: Injuries and illness faced by child workers in Côte d'Ivoire by major industry division

| Industry | Number of workers | Number of injured workers (Wounds and cuts) | Number of ill workers | Total number of injured and ill workers |
|---|---|---|---|---|
| Agriculture | 985600 | 82968 | 37275 | 120243 |
| Manufacturing | 116200 | 7457 | 3350 | 10807 |
| Wholesale, retail, hotel and restaurant | 116200 | 6655 | 2990 | 9645 |
| Community social and personal ervices | 91000 | 4898 | 2200 | 7098 |
| Transport | 53200 | 6644 | 2985 | 9629 |
| Construction | 26600 | 4699 | 2111 | 6810 |
| Mining | 12600 | 1382 | 621 | 2003 |
| **Total** | **1401400** | **114703** | **51532** | **166235** |

We then calculate the health benefits if $166235$ workers were removed child labor. Lets first define variables that will be used in the formular:

1. **q** : percentage of children in child labor
2. **p**: percentage of children eliminated from child labor
3. **For our case we will consider when** $p = q$
4. **N**: Number of children in a country ( for our case is Côte d'Ivoire)
5. **GDP**: Gross Domestic Product
6. **i**: National Central Bank interest rate

We define the formula to calculate the health benefits as:

$$\begin{aligned}\textit{Current value of health cost} =&\% \text{ of children in child labor} \times \text{number of children in a country} \\ &\times 4\% \text{ of GDP} \times \text{present value of the future earnings (20 years)}\end{aligned}$$

The inclusion of 4% of GDP in the given formula serves to account for the economic dimension of health costs related to child labor in line with the estimate of ILO. By incorporating a percentage of the Gross Domestic Product (GDP), it recognizes the portion of a country's overall economic output that is attributed to addressing the health consequences experienced by child laborers. This percentage represents the allocation of resources towards healthcare expenditures associated with child labor-related health issues. Including this factor in the formula enables a comprehensive evaluation of the economic burden incurred by a country due to such health costs, thereby providing a more comprehensive understanding of the overall impact of child labor on the economy(ILO, 2020).

We can rewrite the above equation as follows after the substitution of variables:

$$\boxed{\textit{Current value of health benefits} = \%\ \text{p} \times \text{N} \times 4\% \text{ of GDP} \times \sum_{n=1}^{20} \frac{1}{(1+i)^n}} \tag{3.1}$$

The present of future earnings(10 years) helps in bringing the future benefits back present to better showcase the benefits of the government now.

### 3.1.2 Job opportunities

One approach to measuring the benefits associated with increased job opportunities is by using a formula that takes into account:

- The difference between skilled ($SLW$) and unskilled labor wages ($USLW$)
- The percentage of taxes ($\%t$).

We define the formula of the economic benefits as:

$$\boxed{\begin{aligned}\textit{Current value of potential economic benefits} = &\%\text{of children in child labor} \times \text{number of children in a country} \\ &\times \ \text{(skilled labor salary - unskilled labor salary)} \times \\ &\%\text{ of taxes} \times \text{present value of the future earnings (20 years)}\end{aligned}}$$

We can rewrite the formula as:

$$\boxed{\begin{aligned}\textit{Current value of potential economic benefits} = &\%\ \text{p} \times \text{N} \times (SLW - USLW) \\ &\times \%t \times \sum_{n=1}^{20} \frac{1}{(1+i)^n}\end{aligned}} \tag{3.2}$$

Through this formula, we assume that children no longer in child labor will be better educated, therefore will be more likely to have a skilled job and pay taxes

By using this formula, we can estimate the potential economic benefits of eliminating child labor in a given region or country. However, it is important to note that this formula is only an estimate and that the actual benefits may vary depending on a variety of factors such as local economic conditions, government policies, and the availability of skilled labor. Nonetheless, this formula provides a useful framework for understanding the potential benefits of eliminating child labor and can serve as a starting point for policymakers and researchers who are interested in this issue.

We can combine benefits for the government over $10$ years by combining equations (3.1) and (3.2) as follows:

$$\boxed{\begin{aligned}\textbf{Total benefits for the government} = \%\ \text{p} \times \text{N} \times [4\%GDP + (SLW - USLW) \\ \times \%t] \times \sum_{n=1}^{20} \frac{1}{(1+i)^n}\end{aligned}} \tag{3.3}$$

The formula to find the benefits for the government per child is as follows:

$$\boxed{\textbf{Benefits for the government PER CHILD} = \frac{\text{Total benefits for the government}}{\%p \times N}} \tag{3.4}$$

# 3.2 Data Analysis

## 3.2.1 Data description

The dataset used in this project was from the International Cocoa Initiative (ICI) [2]. It contains data on Côte d'Ivoire, precisely community-level data from a community survey and child labor prevalence results from a household-level child labor prevalence survey. The data was collected between the period: February 02, 2017, to March 03, 2017. Figure 3.1 shows a visualization of the total percentage of children in child labor per region. Variable names used are in short form, refer to Appendix A.1 for full names of variables. The dataset initially contained 172 explanatory variables, which can be found in the appendix, the explanatory variables have 132 observations.

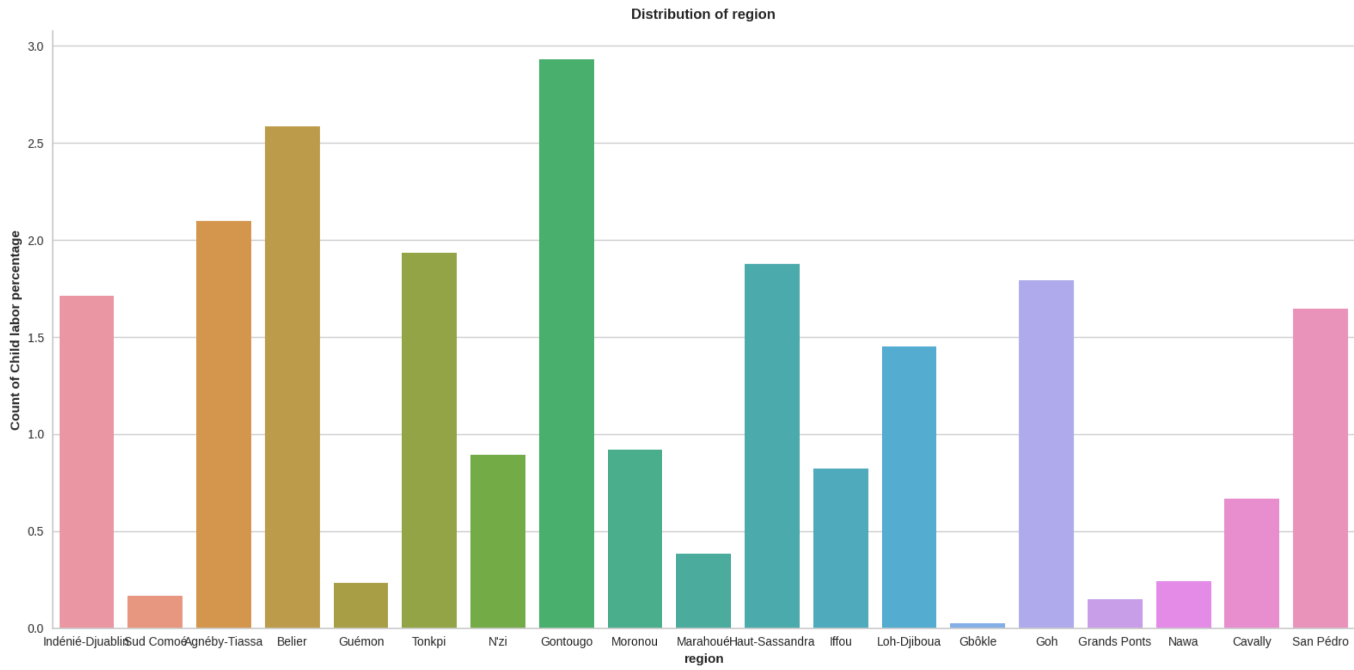


Figure 3.1: Visualisation of the total percentage of children in child labor per region

This graph can assist in understanding the relative occurrence of child labor across different geographic areas. We can see that the region with the highest child labor percentage is "Gontougo".

In this study, the focus is on children aged 5-12 years, which corresponds to the age range typically associated with kindergarten and primary education (Smith et al., 2010). It is well-known that children within this age group attend kindergarten and primary schools as part of their educational journey.

[2]Humanitarian Data Exchange. *Côte d'Ivoire Cocoa Community and Child Labour Data 2017*. Available at: https://data.humdata.org/dataset/C\unhbox\voidb@x\bgroup\let\unhbox\voidb@x\setbox\@tempboxa\hbox{o\global\mathchardef\accent@spacefactor\spacefactor}\let\begingroup\let\typeout\protect\begingroup\def\MessageBreak{Ω(Font)}\let\protect\immediate\write\m@ne{LaTeXFontInfo:\def{}oninputline163.}\endgroup\endgroup\relax\let\ignorespaces\relax\accent94o\egroup\spacefactor\accent@spacefactorte-d-ivoire-cocoa-community-and-child-labour-data-2017. [Accessed 8 May 2023]

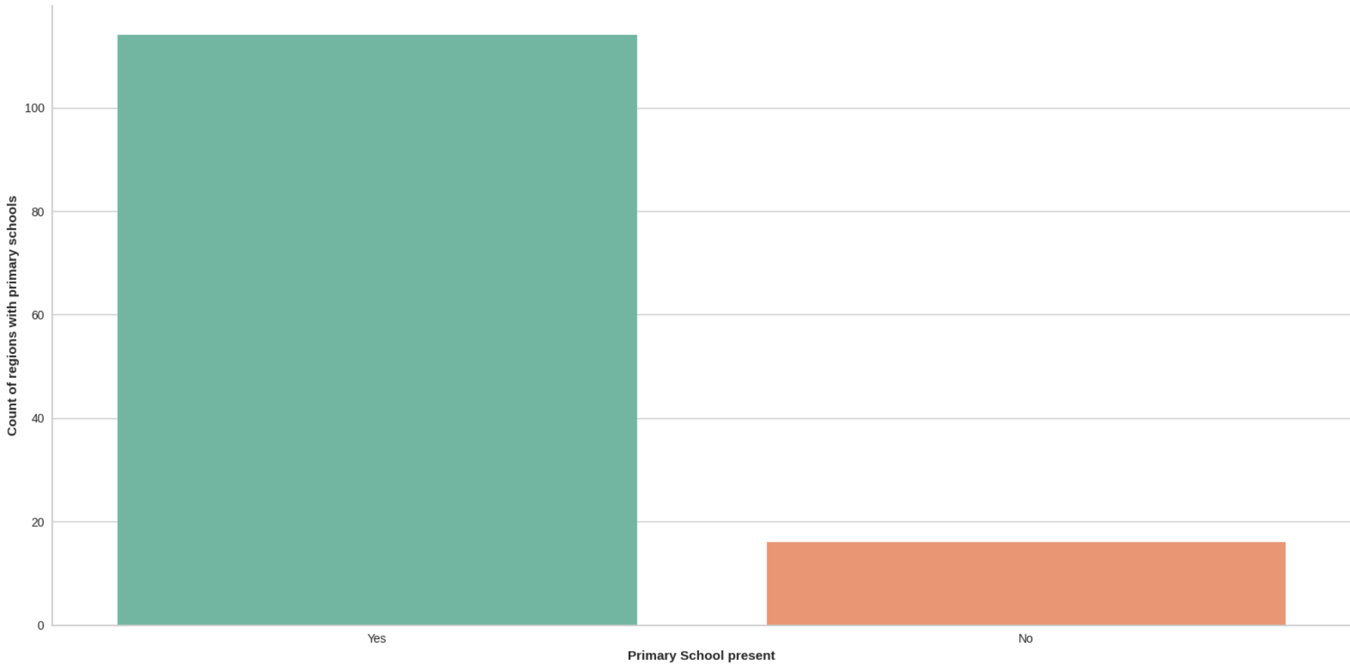


Figure 3.2: Distribution of primary schools

Upon analyzing the plot in Figure 3.2 primary schools, a notable observation emerges: while there are numerous regions with primary schools, the number of those primary schools implementing feeding programs as presented in Figure 3.3, which can play a crucial role in addressing child labor and supporting educational attainment, is relatively low. This finding highlights the potential disparity in access to essential support systems, such as feeding programs, that can alleviate child labor and enhance educational opportunities for children aged $5-12$ years. Further investigation into the reasons behind the variation in the number of primary schools with feeding programs across regions is necessary to address this issue and ensure that more children receive proper nutrition and have the opportunity to pursue education without engaging in child labor.

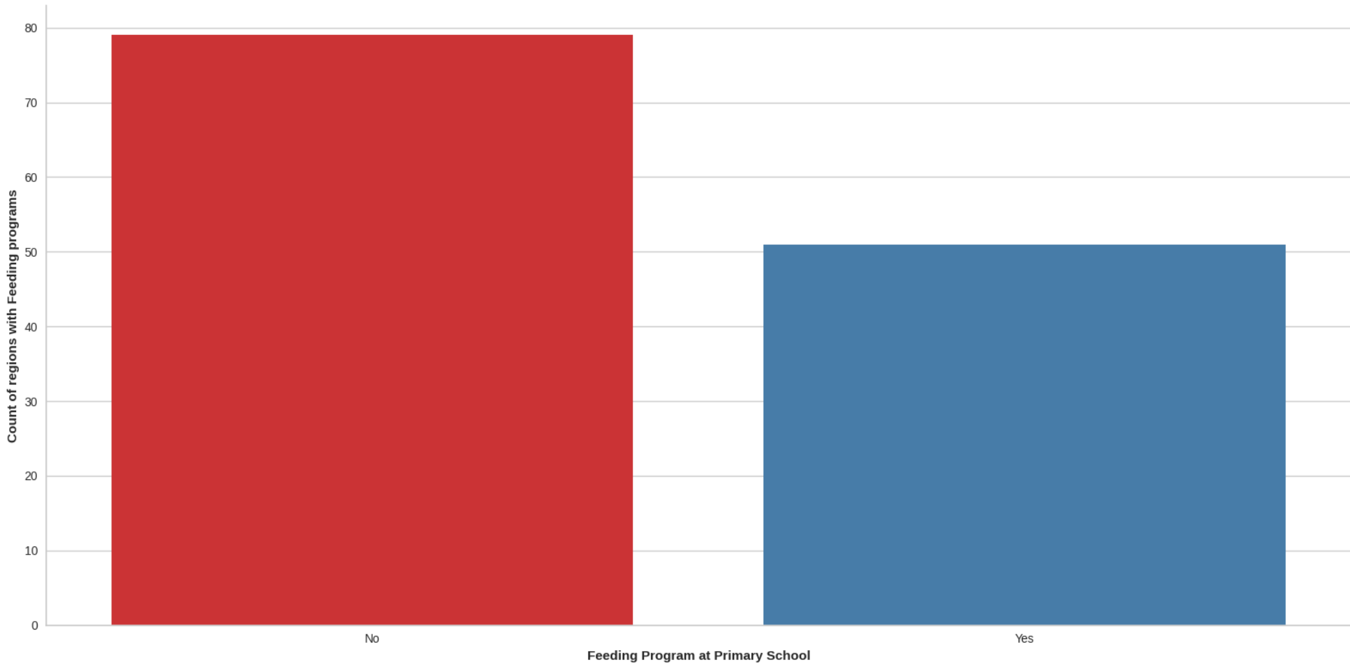


Figure 3.3: Distribution of feeding programs in primary schools

### 3.2.2 Data preprocessing

Real-time datasets often face the problem of missing values, which are values that are not recorded or are incomplete for some observations. This can occur due to a variety of reasons, such as sensor malfunction, data transmission errors, or simply because the data was not collected for a specific observation. Missing values can be problematic because they can affect the accuracy and reliability of any analysis performed on the data. For example, if a large number of observations have missing values, it can lead to biased or incomplete results, making it difficult to draw meaningful conclusions from the data.

To address this issue, it is important to implement appropriate methods for handling missing values in real-time datasets. One common approach is to use imputation techniques, which involve estimating the missing values based on the values of other variables in the dataset.

**Imputation method**

Missing values pose a significant challenge when analyzing economic datasets. To ensure the accuracy and reliability of our statistical analysis, we employ a robust technique called imputation with random forests. This approach allows us to address missing values in our dataset, enabling a comprehensive examination of the economic benefits associated with the elimination of child labor in Côte d'Ivoire.

The imputation process using random forests consists of the following steps, tailored to our project's focus on child labor:

1. Identification of missing values: Our dataset is thoroughly inspected to identify missing values. These missing values could be the result of incomplete data collection or other factors.

2. Splitting the dataset: The dataset is partitioned into two subsets: one comprising complete observations, and the other containing observations with missing values. The complete observations serve as the training set, while the subset with missing values becomes the target set for imputation.

3. Training the random forest Model: A random forest model is trained using the complete observations from our dataset. The random forest algorithm constructs an ensemble of decision trees, which collectively make accurate predictions. In our project, the model is trained to predict variables related to economic indicators, labor statistics, and child welfare using the remaining variables available.

4. Prediction of missing values: Once the random forest model is trained, it is applied to predict the missing values in the target set. For each missing value, the corresponding features (e.g., GDP, education indicators) are fed into the trained random forest model. The model leverages the observed data to generate predicted values for the missing data points.

5. Replacement of missing values: The predicted values obtained from the random forest model are substituted for the missing values in the dataset. By imputing the missing values, we ensure that our analysis encompasses a complete dataset, providing a more comprehensive understanding of the economic benefits of eliminating child labor in Côte d'Ivoire.

The imputation process relies on the underlying algorithms of random forests and their mathematical formulations. Here are the key equations involved:

**3.2.1 Definition. Gini Impurity**: *Gini impurity is a measure of impurity or disorder within a node of a decision tree. It is calculated as follows:*

$$Gini(p) = 1 - \sum_{i=1}^{k}(p_i^2) \tag{3.5}$$

*where $p_i$ $(p_1, p_1, \ldots, p_k)$ represents the probability being in each class. The summation is taken over all classes and $k$ is the number of observations. This impurity measure is used by the random forest algorithm during the construction of decision trees.*

**3.2.2 Definition. Entropy**: *Entropy is another measure of impurity used in decision tree algorithms. It is given by the equation:*

$$H(X) = -\sum_{x\in\mathcal{X}} P(x)\log_2 P(x),$$

*where $\mathcal{X}$ represents the set of possible values of $X$ and $P(x)$ is the probability of observing the value $x$. The logarithm base $2$ is commonly used, resulting in entropy measured in bits. A bit is a fundamental unit of information, and measuring entropy in bits allows us to quantify the information content of the variable X in binary form.*

*In continuous distributions, the entropy is defined using probability density functions:*

$$H(X) = -\int_{x\in\mathcal{X}} p(x)\log_2 p(x)\,dx$$

*where $p(x)$ is the probability density function of $X$.*

*The entropy provides a measure of the amount of information or uncertainty contained in a random variable. When the entropy value is higher, it means there is more uncertainty or randomness in the situation. This implies that the outcomes are less predictable and have a wider range of possibilities. On the other hand, when the entropy value is lower, it indicates more predictability or organization. In this case, the outcomes are more likely to fall into a specific pattern or a smaller set of possibilities. Essentially, entropy serves as a measure of how much surprise or information is associated with the potential outcomes of a random variable.*

**3.2.3 Definition. Random Forest Prediction** *In a random forest, predictions from multiple decision trees are combined to make the final prediction. The method differs depending on the task at hand:*

*For classification tasks, the majority voting formula is used:*

$$\textit{Prediction} = \textit{argmax}\left(\sum_i w_i \cdot I(y_i = \textit{class})\right),$$

*where $w_i$ denotes the weight or importance assigned to each tree, $y_i$ represents the predicted class from each tree and $I(\cdot)$ is the indicator function.*

*For regression tasks, the predictions are averaged:*

$$\textit{Prediction} = \sum_i w_i \cdot y_i,$$

*Here, $w_i$ represents the weight or importance assigned to each tree, and $y_i$ is the predicted value from each tree.*

*These mathematical formulas elucidate the fundamental concepts and computations involved in the imputation process with random forests. It is important to note that specific software or libraries may implement variations of these equations. Nonetheless, the overall approach remains consistent in leveraging random forests for imputing missing values in economic datasets.*

By utilizing these mathematical formulas and leveraging the power of random forests for imputation, we can ensure that our analysis of the economic benefits of eliminating child labor in Côte d'Ivoire is based on a complete and reliable dataset. This enables us to gain valuable insights into the potential positive impacts on economic indicators and societal well-being that can be achieved through effective measures to eradicate child labor.

### 3.2.3 Significant variables

We present the results of our data analysis to identify the variables that have a significant impact on the percentage of child labor in Côte d'Ivoire districts. Identifying these variables is crucial for policymakers and stakeholders who are working to eliminate child labor, as it allows them to target interventions more effectively. We used various feature engineerings methods such as mutual information, correlation analysis, and regression models to identify the most important variables. By examining the relationships between these variables and child labor rates, we were able to gain insights into the underlying drivers of child labor in Côte d'Ivoire.

#### Mutual information approach

Mutual information is a widely used feature engineering technique for identifying the relationship between two variables. It is a measure of the mutual dependence between two variables and is calculated by assessing the amount of information that one variable provides about the other. In the context of our analysis, we used mutual information to measure the strength of the relationship between each predictor variable and the percentage of child labor in Côte d'Ivoire districts. The mutual information between two random variables $X$and $Y$ is defined as follows:

$$I(X;Y) = H(X) - H(X|Y)$$

where $H(X)$ is the entropy of $X$, and $H(X|Y)$ is the conditional entropy of $X$ given $Y$. The entropy can be calculated in the same way as defined in Definition 3.2.2.

To calculate the mutual information between each predictor variable and the percentage of child labor in Cote d'Ivoire districts, we first discretized each continuous variable into a set of bins using the equal frequency binning method. We then calculated the joint probability mass function of each predictor variable and the target variable, as well as the probability mass function of each variable. Finally, we used these probabilities to calculate the mutual information using the equations above. After calculating probabilities, the probabilities were as follows in Table 3.3 and we considered the ones with probability different from 0 and we took the first 24 variables. We can see visually see the graph that shows the first significant variable which is the distance to the nearest secondary healthcare facility (health secondary d) since it can have a significant impact on the health and well-being of children and the economic development of the community.

Mutual information scores for the top 24 variables with scores different from 0 are provided in Table 3.3

| Feature | MI Score |
|---|---|
| distance to nearest secondary healthcare facility (health_secondary_d) | 0.160872 |
| distance to nearest senior high (shigh_d) | 0.15707 |
| distance to nearest kindergarten (kinderg_d) | 0.147451 |
| percentage of women with children¡5 in the community (women_percchild05) | 0.129109 |
| Male drop out rate in Primary 1 (CED_bdropout_prim1) | 0.126269 |
| District name (district) | 0.125096 |
| children enrolled vocational (N_ch_voc) | 0.118892 |
| main education level of men in the community (men_edu) | 0.112738 |
| boys enrolled vocational (N_bch_voc ) | 0.108862 |
| distance to nearest primary healthcare centre | 0.098813 |
| percentage of women engaged in livelihood activities apart from cocoa (women_percliv ) | 0.098556 |
| girls enrolled vocational (N_gch_voc ) | 0.092899 |
| percentage of men that can read in the community (men_percread) | 0.091633 |
| main education level of women in the community (women_edu) | 0.089212 |
| distance to nearest junior high (jhigh_d) | 0.086214 |
| Male children enrolled in Primary 4 (CED_N_bch_prim4) | 0.075064 |
| number of primary schools (primary_n) | 0.074658 |
| Female attendance rate in Primary 1 (CED_gattend_prim1) | 0.067734 |
| Farming inputs affordable in the community (input_af) | 0.066594 |
| Farm labor cost per day (casualwork_cost) | 0.065196 |
| percentage of women with no formal education in the community (women_percnoed) | 0.0632 |
| Region name (region) | 0.056958 |
| Percentage of women owning and cultivating land in the community (women_perclandcul) | 0.051764 |

Table 3.3: Mutual information scores for the top 24 variables with their scores

We can see visually in the graph 3.4 that shows the first significant variable which is **distance to a nearest secondary healthcare facility (**$health\_secondary\_d$**)** since it can have a significant impact on the health and well-being of children and the economic development of the community.

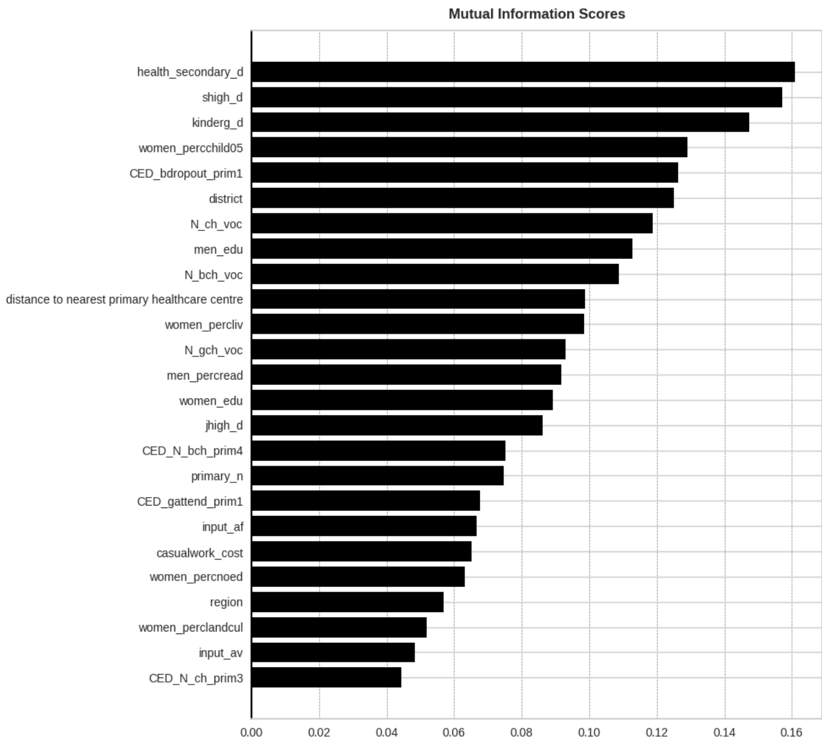


Figure 3.4: Mutual information scores fpr the top 24 variables

For instance, consider the predictor variable "percentage of women with children less than 5 years in the community (women_percchild05)" and the target variable "percentage of Child Labor (lcommp_clab)". We first discretized "women_percchild05" into 4 equal frequency bins because women_percchild05 has four classes which are the percentage of women with children less than 5 years: $0 - 30$, $61 - 80$, $31 - 60$, and $81 - 100$ as in Figure 3.5. We then calculated the joint probability mass function of women_percchild05 and lcommp_clab by counting the number of observations in each bin for each variable and dividing by the total number of observations. We also calculated the probability mass function of each variable by summing the joint probability mass function over the bins for that variable. Finally, we used these probabilities to calculate the mutual information between "women_percchild05" and "lcommp_clab" using the equations above.

Figure 3.6 plots a linear regression model between the feature "N_ch_kinderg" and the percentage of child labor "lcommp_clab" to show the detection of a relationship by mutual information. The data points are colored based on the percentage of women with children under 5 years old.

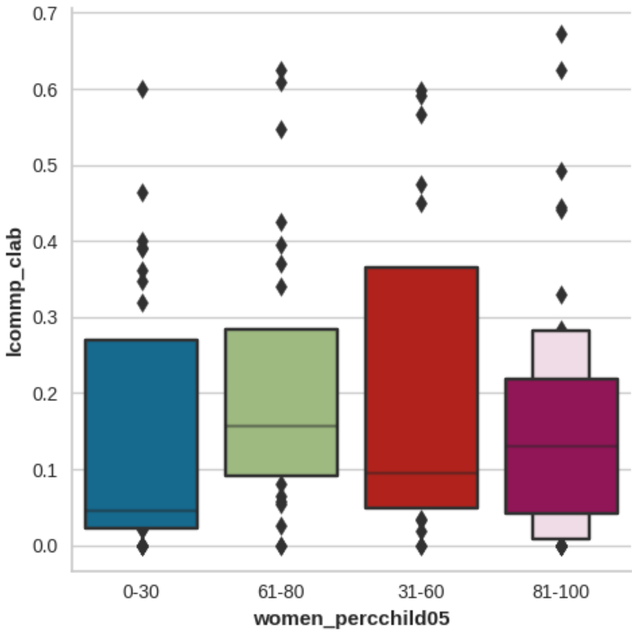


Figure 3.5: Percentage of women who have children of age less than $5$ years

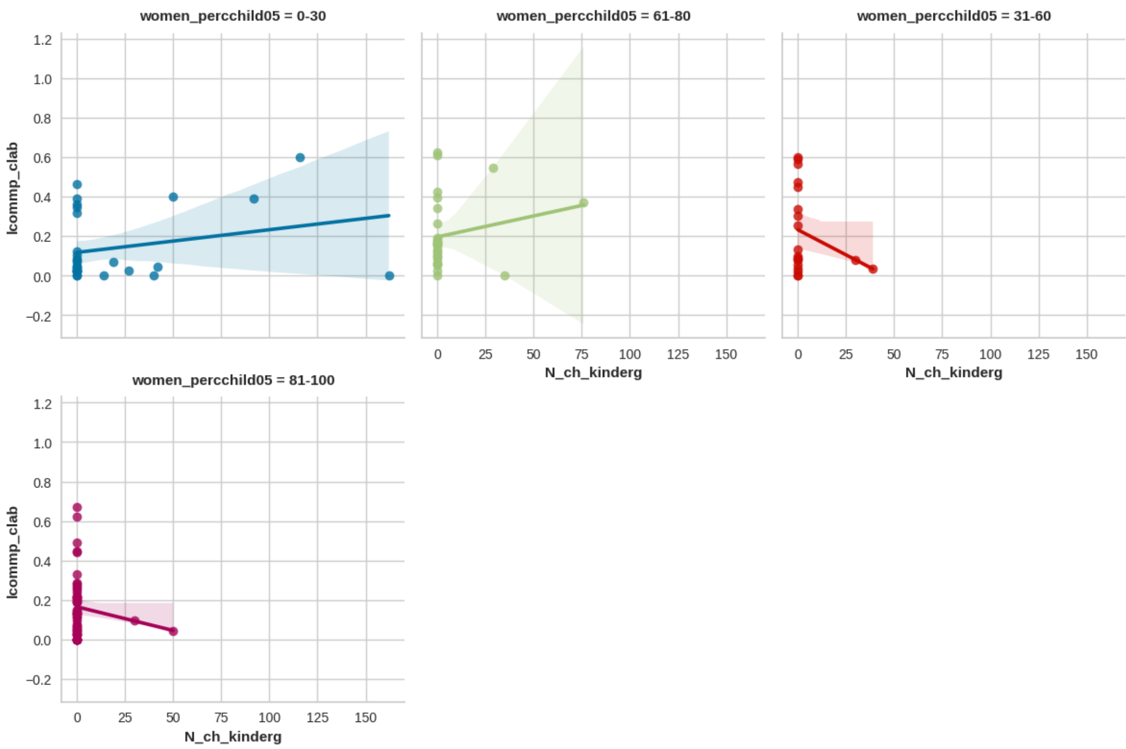


Figure 3.6: Relationship of % of children in child labor and % of women with children under 5 years for four percentage classes

### 3.2.4 Regression model

We will be using a linear regression model with Ordinary Least Squares (OLS) to determine the key determinants of the percentage of children in child labor per district in Côte d'Ivoire. The regression model will help us understand the relationship between the independent variables and the dependent variable.

Our dataset consists of several independent variables such as household income, education level, access to basic amenities, and the prevalence of child labor laws, among others. The dependent variable in this study is the percentage of children in child labor per district. By analyzing the relationship between these variables, we aim to identify the key determinants that contribute to child labor in Côte d'Ivoire and suggest potential policy interventions.

We employ a multiple linear regression model to estimate the relationship between the percentage of children in child labor per district and a set of explanatory variables. Let $Y$ be the percentage of children in child labor in a given district, and let $X_{1i}, X_{2i}, ..., X_{ki}$ represent a vector of $k$ explanatory variables for district $i$. We can then express the linear regression model as:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{1k} + \epsilon_i,$$

Where:

- $\beta_0$ is the intercept
- $\beta_1, \beta_2, ..., \beta_k$ are the coefficients for the explanatory variables. We can express this as a row matrix:

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_n \end{bmatrix}$$

- We can express the explanatory variables for all districts as a matrix $X$ :

$$X = \begin{bmatrix} X_{11} & X_{21} & \cdots & X_{n1} \\ X_{12} & X_{22} & \cdots & X_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ X_{1k} & X_{2k} & \cdots & X_{nk} \end{bmatrix}$$

- $\epsilon_i$ is the error term. We can express the error term as a column vector:

$$\epsilon = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}.$$

Let's rewrite the regression model as follows:

$$Y = \beta X + \epsilon$$

**OUR GOAL**: Our goal is to find the values of $\beta$ that minimize the sum of squared errors, also known as the residual sum of squares (RSS):

$$RSS = \sum_{i=1}^{n} \epsilon_i^2 = \sum_{i=1}^{n} (Y_i - X_i\beta)^2.$$

To do this, we use the method of Ordinary Least Squares (OLS). The OLS method estimates the coefficients $\beta$ by minimizing the sum of squared errors, which can be expressed as:

$$\min_{\beta} \sum_{i=1}^{n} (Y_i - X_i\beta)^2.$$

This optimization problem can be solved by taking the first derivative of the RSS with respect to $\beta$, setting it equal to zero, and solving for $\beta$. The resulting OLS estimates are given by:

$$\hat{\beta} = (X^T X)^{-1} X^T Y_i$$

We can use the estimated coefficients $\hat{\beta}$ to make predictions for new values of the independent variables. For example, if we want to predict the percentage of children in child labor in a district with household income $X_{i,1}$ and education level $X_{i,2}$, we can calculate the predicted value of $Y$ as:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{i,1} + \hat{\beta}_2 X_{i,2} + ... + \hat{\beta}_p X_{i,p}$$

where $\hat{\beta}_0$ is the intercept term, and $\hat{\beta}_j$ is the estimated coefficient for the $j^{th}$ independent variable.

The OLS estimates provide the values of $\beta$ that minimize the RSS, which in turn represents the best linear approximation of the relationship between $X$ and $Y_i$. This allows us to make predictions for new values of $Y$ based on the estimated coefficients $\hat{\beta}$. Additionally, the OLS method provides a number of diagnostic statistics that can be used to evaluate the goodness of fit of the regression model and to check for violations of the underlying assumptions.

The assumptions are:

1. Linearity: The relationship between the independent variables (denoted as $X$) and the dependent variable (denoted as $Y$) is assumed to be linear. Mathematically, this assumption can be written as: $Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p + \epsilon_1$

   where $Y$ is the dependent variable, $X_1, X_2, \ldots, X_p$ are the independent variables, $\beta_0, \beta_1, \beta_2, \ldots, \beta_p$ are the coefficients (or parameters) representing the effect of each independent variable, and $\epsilon$ is the error term.

2. Independence: The observations in the dataset are assumed to be independent of each other. Mathematically, this means that the errors or residuals (denoted as $\epsilon$) for different observations are uncorrelated. In other words, for any pair of observations $i$ and $j$ (where $i \neq j$), the covariance between their residuals is zero: $\text{Cov}(\epsilon_i, \epsilon_j) = 0$.

3. Homoscedasticity: The variability of the residuals (denoted as $\epsilon$) should be constant across all levels of the independent variables. Mathematically, this assumption can be written as: $\text{Var}(\epsilon) = \sigma^2$

   where $\text{Var}(\epsilon)$ represents the variance of the residuals and $\sigma^2$ is a constant value.

4. Normality: The residuals are assumed to follow a normal distribution. Mathematically, this means that the errors or residuals (denoted as $\epsilon$) are normally distributed with a mean of zero and constant variance. This assumption can be written as:

$$\epsilon \sim \mathcal{N}(0, \sigma^2)$$

   where $\epsilon$ follows a normal distribution with a mean of zero and variance $\sigma^2$.

5. No multicollinearity: The independent variables should not be highly correlated with each other. Mathematically, this assumption is often assessed using the variance inflation factor (VIF) or correlation matrix to detect high levels of multicollinearity. The diagnostic statistics provided by the OLS method, such as R-squared, t-tests, F-tests, residuals analysis, and variance inflation factor (VIF), are used to assess the adherence of the data and model to these assumptions. They help evaluate the overall goodness of fit of the regression model and identify potential violations of these underlying assumptions.

### 3.2.5 Metric Evaluation

The evaluation of the regression model is essential to gauge its reliability and suitability for understanding the economic benefits of eliminating child labor. In this section, we employ a comprehensive set of metrics to assess the performance and goodness of fit of our regression model. These metrics provide valuable insights into the explanatory power, significance, and overall quality of the model. By defining each metric and presenting their corresponding mathematical expressions, we aim to provide a rigorous evaluation framework. As follows we have definitions of some metrics to be used:

**3.2.4 Definition. R-squared:** *The R-squared metric represents the proportion of variance in the dependent variable explained by the regression model. It is calculated as the ratio of the explained variation to the total variation. The mathematical formula for R-squared is given by:*

$$R^2 = \frac{\textit{Explained Variation}}{\textit{Total Variation}}$$

*A higher R-squared value indicates that the model captures a larger portion of the variation in the dependent variable. In the context of eliminating child labor, a higher R-squared can suggest a better understanding of the factors influencing child labor and their potential economic impact.*

**3.2.5 Definition. Adj. R-squared:** *The adjusted R-squared takes into account the number of predictors in the regression model, providing a more balanced measure of model complexity and explanatory power. The formula for adjusted R-squared is given by:*

$$\text{Adj. } R^2 = 1 - \left(1 - R^2\right) \cdot \frac{n-1}{n-p-1}$$

*Here, $n$ represents the number of observations and $p$ represents the number of predictors. A higher adjusted R-squared value indicates a better balance between model fit and complexity.*

**3.2.6 Definition. F-statistic:** *The F-statistic assesses the overall significance of the regression model. It compares the explained variation (variation accounted for by the model) to the unexplained variation (residual variation). The mathematical formula for the F-statistic is given by:*

$$F = \frac{\text{Explained Variation / df1}}{\text{Unexplained Variation / df2}}$$

*The F-statistic is used to test the null hypothesis that all regression coefficients are equal to zero. A higher F-statistic suggests a stronger relationship between the independent variables and the dependent variable. In the context of child labor elimination, a significant F-statistic may indicate meaningful economic relationships.*

**3.2.7 Definition. Prob (F-statistic):** *The probability associated with the F-statistic represents the likelihood of observing the F-statistic under the null hypothesis. A low probability (typically below a chosen significance level) indicates that the observed relationship between the independent variables and the dependent variable is unlikely due to chance. This suggests a meaningful connection between factors influencing child labor and potential economic benefits that could be gained from eliminating child labor.*

**3.2.8 Definition. Log-Likelihood:** *The log-likelihood represents the log of the likelihood function of the regression model. It is used in model comparisons and hypothesis testing. While it does not directly relate to economic benefits, the log-likelihood helps evaluate the goodness of fit of the model and allows for meaningful comparisons with alternative models.*

**3.2.9 Definition. AIC (Akaike Information Criterion):** *The AIC is a measure of the model's quality and complexity. It is calculated as -2 times the log likelihood plus 2 times the number of parameters in the model. The formula for AIC is given by:*

$$\text{AIC} = -2 \times \text{Log-Likelihood} + 2 \times \text{Number of Parameters}$$

*A lower AIC value indicates a better balance between model fit and complexity. In the context of eliminating child labor, a lower AIC suggests a more parsimonious model that captures important economic relationships.*

These metrics encompass measures of various goodness-of-fit indicators. The understanding of these metrics will allow us to interpret the results accurately, assess the economic benefits associated with eliminating child labor, and derive meaningful policy implications based on sound statistical evidence.

# 4. Results and discussion

## 4.1 Regression results

### 4.1.1 Analysis of the accuracy:

To obtain Table 4.1, a regression model was tuned and evaluated. The goal of the tuning process was to optimize the model's performance and enhance its ability to predict the dependent variable, named "lcommp clab."

The tuning process likely involved adjusting various parameters and configurations of the regression model. These adjustments could include selecting the appropriate set of independent variables, choosing the functional form of the model, and determining the appropriate weighting scheme, among other considerations.

Once the model was tuned, it was evaluated using various metrics and statistics to assess its performance. The table presents the results of this evaluation, providing insights into the model's goodness of fit and statistical properties.

| | | | |
|---|---|---|---|
| **Dep. Variable:** | lcommp_clab | **R-squared:** | 0.999 |
| **Model:** | OLS | **Adj. R-squared:** | 0.956 |
| **Method:** | Least Squares | **F-statistic:** | 23.21 |
| **Date:** | Fri, 12 May 2023 | **Prob (F-statistic):** | 0.0120 |
| **Time:** | 10:38:04 | **Log-Likelihood:** | 345.24 |
| **No. Observations:** | 97 | **AIC:** | -502.5 |
| **Df Residuals:** | 3 | **BIC:** | -260.5 |
| **Df Model:** | 93 | **Durbin-Watson:** | 1.762 |
| **Covariance Type:** | nonrobust | **Jarque-Bera (JB):** | 199.709 |
| **Omnibus:** | 23.629 | **Prob(JB):** | 4.30e-44 |
| **Prob(Omnibus):** | 0.000 | **Cond. No.** | 1.00e+16 |
| **Skew:** | 0.011 | **Kurtosis:** | 10.029 |

Table 4.1: Summary table of regression model metrics

Based on the provided OLS model summary, we can interpret several metrics that aid in explaining the regression model using the methodology of these metrics as in section 3.2.5. These metrics include:

1. Dependent Variable: The dependent variable in the regression model is denoted as "lcommp_clab."

This variable represents the response or outcome variable that you are trying to predict or explain using the independent variables.

2. R-squared: The R-squared value measures the proportion of the variance in the dependent variable that is explained by the independent variables. In this case, the R-squared value is 0.999, indicating that approximately 99.9% of the variability in the dependent variable is accounted for by the independent variables included in the model. A higher R-squared value suggests a better fit of the model to the data.

3. Model: The model used in this analysis is an OLS (Ordinary Least Squares) regression model. OLS is a commonly used technique to estimate the parameters of a linear regression model by minimizing the sum of squared residuals.

4. Adj. R-squared: The adjusted R-squared value adjusts the R-squared value by the number of independent variables and the sample size. It provides a more conservative measure of the model's goodness of fit by penalizing the inclusion of unnecessary variables. In this case, the adjusted R-squared is 0.956.

5. Method: The method employed in this analysis is Least Squares, which is the standard approach for estimating the coefficients of a linear regression model.

6. F-statistic: The F-statistic tests the overall significance of the regression model. It determines whether the independent variables, as a group, have a significant effect on the dependent variable. A higher F-statistic value suggests a stronger overall relationship between the independent and dependent variables. Here, the F-statistic is 23.21.

7. Prob (F-statistic): This value represents the p-value associated with the F-statistic. It indicates the probability of observing an F-statistic as extreme as the one computed under the null hypothesis of no relationship between the independent and dependent variables. In this case, the p-value is 0.0120, which is below the conventional threshold of 0.05, suggesting that the independent variables are collectively significant.

8. Date and Time: These indicate the date and time when the regression analysis was conducted.

9. Log-Likelihood: The log-likelihood is a measure of how well the regression model predicts the observed data. It quantifies the likelihood of observing the data given the estimated model. A higher log-likelihood value indicates a better fit of the model to the data. In this case, the log-likelihood is 345.24.

10. No. Observations: This represents the number of observations used in the regression analysis. In this case, there are 97 observations.

11. AIC and BIC: These are information criteria used for model selection. AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) are measures that balance the goodness of fit of the model with the complexity of the model. Lower values of AIC and BIC indicate better-fitting models. In this case, the AIC is -502.5 and the BIC is -260.5.

12. Df Residuals and Df Model: Df Residuals refers to the degrees of freedom of the residuals, which is the difference between the total number of observations and the number of parameters estimated in the model. Df Model represents the degrees of freedom associated with the independent variables.

13. Durbin-Watson: The Durbin-Watson statistic is used to test for the presence of autocorrelation in the residuals of a regression model. It takes values between 0 and 4, where a value around 2 suggests no autocorrelation. In this case, the Durbin-Watson statistic is 1.762.

14. Covariance Type: This indicates the type of covariance estimation used in the regression model. In this case, the covariance type is nonrobust.

15. Jarque-Bera (JB): The Jarque-Bera statistic is a test for the normality of the residuals in the regression model. It assesses whether the residuals follow a normal distribution. Higher values of JB indicate departures from normality. Here, the JB statistic is 199.709.

16. Omnibus and Prob(Omnibus): The Omnibus test is a combined test for skewness and kurtosis of the residuals. It tests the null hypothesis that the residuals are normally distributed. The Prob(Omnibus) value provides the associated p-value. In this case, the Omnibus statistic is 23.629, and the p-value is 0.000, indicating the non-normality of the residuals.

17. Skew and Kurtosis: Skewness measures the asymmetry of the residuals' distribution. A skewness value close to zero indicates a symmetric distribution. Kurtosis measures the heaviness of the tails of the distribution. A kurtosis value of 3 represents a normal distribution. In this case, the residuals have a very small skewness of 0.011 and a kurtosis of 10.029, indicating some departure from normality and heavy tails.

Overall, these metrics suggest that the model is a good fit for the data, with a high R-squared value and statistically significant independent variables. However, the large number of independent variables (93) and the small sample size (97) suggest that caution should be exercised when interpreting the results.

### 4.1.2 Discussion

In the OLS summary table, the p-value measures the strength of evidence against the null hypothesis that the true population coefficient of a variable is equal to zero. A p-value less than 0.05 indicates that the evidence against the null hypothesis is strong, and the variable is considered statistically significant at the 5% level.

Therefore, to select significant variables, we typically look for the ones with p-values less than 0.05. These variables have a significant relationship with the outcome variable and should be included in the model. On the other hand, variables with p-values greater than 0.05 are not statistically significant, and their coefficients are not significantly different from zero, meaning they can be removed from the model without affecting its predictive power.

In the regression analysis, several variables were found to be statistically significant at the 5% level, meaning that they have a significant impact on the elimination of child labor in Côte d'Ivoire. Table 3.3 shows to see the variables whose p-value is less than $0.05$.

| | coef | std err | t | P>$\|t\|$ | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **kinderg_d** | -1.380000e-02 | 2.000000e-03 | -6.159 | 0.009 | -2.100000e-02 | -7.000000e-03 |
| **N_gch_voc** | 1.830000e-02 | 6.000000e-03 | 3.240 | 0.048 | 0.000000e+00 | 3.600000e-02 |
| **women_percchild05_31-60** | 2.550000e-01 | 6.000000e-02 | 4.285 | 0.023 | 6.600000e-02 | 4.440000e-01 |
| **women_percchild05_61-80** | -1.279000e-01 | 3.300000e-02 | -3.829 | 0.031 | -2.340000e-01 | -2.200000e-02 |
| **district_Agboville** | -1.069000e-15 | 2.580000e-16 | -4.139 | 0.026 | -1.890000e-15 | -2.470000e-16 |
| **district_Alépé** | -4.720000e-01 | 1.120000e-01 | -4.214 | 0.024 | -8.290000e-01 | -1.160000e-01 |
| **district_Attiégouakro** | 2.570000e-01 | 7.200000e-02 | 3.569 | 0.038 | 2.800000e-02 | 4.860000e-01 |
| **district_Bangolo** | 7.099000e-01 | 1.300000e-01 | 5.473 | 0.012 | 2.970000e-01 | 1.123000e+00 |
| **district_Bocanda** | 4.486000e-01 | 5.800000e-02 | 7.695 | 0.005 | 2.630000e-01 | 6.340000e-01 |
| **district_Bondoukou** | -5.173000e-01 | 8.400000e-02 | -6.161 | 0.009 | -7.840000e-01 | -2.500000e-01 |
| **district_Bongouanou** | 5.971000e-01 | 8.800000e-02 | 6.796 | 0.007 | 3.170000e-01 | 8.770000e-01 |
| **district_Daoukro** | 1.342200e+00 | 1.230000e-01 | 10.947 | 0.002 | 9.520000e-01 | 1.732000e+00 |
| **district_Dimbokro** | -4.791000e-01 | 8.200000e-02 | -5.838 | 0.010 | -7.400000e-01 | -2.180000e-01 |
| **district_Divo** | -3.300000e-01 | 9.800000e-02 | -3.359 | 0.044 | -6.430000e-01 | -1.700000e-02 |
| **district_Duekoué** | -4.080000e-01 | 8.300000e-02 | -4.935 | 0.016 | -6.710000e-01 | -1.450000e-01 |
| **district_Facobly** | -2.792000e-01 | 8.000000e-02 | -3.509 | 0.039 | -5.330000e-01 | -2.600000e-02 |
| **district_Guéyo** | 7.907000e-01 | 1.100000e-01 | 7.156 | 0.006 | 4.390000e-01 | 1.142000e+00 |
| **district_Issia** | -7.201000e-01 | 1.950000e-01 | -3.695 | 0.034 | -1.340000e+00 | -1.000000e-01 |
| **district_Jacqueville** | -1.005700e+00 | 1.600000e-01 | -6.285 | 0.008 | -1.515000e+00 | -4.960000e-01 |
| **district _Kouassi-Kouassikro** | -9.414000e-01 | 1.610000e-01 | -5.864 | 0.010 | -1.452000e+00 | -4.300000e-01 |
| **district_Kouibly** | -3.158000e-01 | 7.800000e-02 | -4.049 | 0.027 | -5.640000e-01 | -6.800000e-02 |
| **district_Lakota** | -7.119000e-01 | 1.670000e-01 | -4.258 | 0.024 | -1.244000e+00 | -1.800000e-01 |
| **district_Prikro** | 5.868000e-01 | 1.150000e-01 | 5.120 | 0.014 | 2.220000e-01 | 9.520000e-01 |
| **district_Sandégué** | 1.313600e+00 | 2.380000e-01 | 5.525 | 0.012 | 5.570000e-01 | 2.070000e+00 |
| **district_Sassandra** | -1.572400e+00 | 1.990000e-01 | -7.910 | 0.004 | -2.205000e+00 | -9.400000e-01 |
| **district_Sinfra** | -4.973000e-01 | 1.520000e-01 | -3.265 | 0.047 | -9.820000e-01 | -1.300000e-02 |
| **district_Sipilou** | -2.901700e+00 | 3.400000e-01 | -8.533 | 0.003 | -3.984000e+00 | -1.820000e+00 |
| **district_Taabo** | 1.000400e+00 | 1.050000e-01 | 9.531 | 0.002 | 6.660000e-01 | 1.334000e+00 |
| **district_Tabou** | 2.120000e-01 | 5.800000e-02 | 3.681 | 0.035 | 2.900000e-02 | 3.950000e-01 |

The first variable, kinderg_d, has a negative coefficient of -0.0138, meaning that as the number of kindergartens in the area increases, the incidence of child labor decreases. This is expected because kindergartens provide early education to children and help them develop the skills necessary to

| | coef | std err | t | P>$\|t\|$ | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **district_Tanda** | 5.630000e-01 | 9.500000e-02 | 5.923 | 0.010 | 2.600000e-01 | 8.650000e-01 |
| **district_Tiapoum** | -3.925000e-01 | 1.200000e-01 | -3.280 | 0.046 | -7.730000e-01 | -1.200000e-02 |
| **district_Tiébissou** | 3.619000e-01 | 7.300000e-02 | 4.947 | 0.016 | 1.290000e-01 | 5.950000e-01 |
| **district_Toumodi** | -3.844000e-01 | 7.500000e-02 | -5.113 | 0.014 | -6.240000e-01 | -1.450000e-01 |
| **district_Vavoua** | 6.362000e-01 | 9.100000e-02 | 6.971 | 0.006 | 3.460000e-01 | 9.270000e-01 |
| **district_Yakassé-Attobrou** | 4.963000e-01 | 1.220000e-01 | 4.054 | 0.027 | 1.070000e-01 | 8.860000e-01 |
| **district_Zoukougbeu** | 5.247000e-01 | 7.000000e-02 | 7.496 | 0.005 | 3.020000e-01 | 7.470000e-01 |
| **men_edu_Junior High School** | -2.975000e-01 | 4.300000e-02 | -6.976 | 0.006 | -4.330000e-01 | -1.620000e-01 |
| **men_edu_No school** | 1.151300e+00 | 9.700000e-02 | 11.928 | 0.001 | 8.440000e-01 | 1.458000e+00 |
| **men_edu_Primary 1-3** | 3.915000e-01 | 7.000000e-02 | 5.564 | 0.011 | 1.680000e-01 | 6.160000e-01 |
| **men_edu_Primary 4-6** | -1.330000e-01 | 3.900000e-02 | -3.375 | 0.043 | -2.580000e-01 | -8.000000e-03 |
| **men_edu_Senior High School** | -2.528000e-01 | 6.900000e-02 | -3.661 | 0.035 | -4.730000e-01 | -3.300000e-02 |
| **men_edu_University** | -2.793000e-01 | 6.800000e-02 | -4.131 | 0.026 | -4.950000e-01 | -6.400000e-02 |
| **men_edu_Vocational/technical** | -2.882000e-01 | 8.700000e-02 | -3.313 | 0.045 | -5.650000e-01 | -1.100000e-02 |
| **women_percliv_61-80** | -1.532000e-01 | 3.300000e-02 | -4.587 | 0.019 | -2.590000e-01 | -4.700000e-02 |
| **women_percliv_81-100** | 3.333000e-01 | 4.500000e-02 | 7.357 | 0.005 | 1.890000e-01 | 4.780000e-01 |
| **men_percread_31-60** | -2.866000e-01 | 4.900000e-02 | -5.825 | 0.010 | -4.430000e-01 | -1.300000e-01 |
| **men_percread_61-80** | 1.045000e-01 | 3.000000e-02 | 3.432 | 0.041 | 8.000000e-03 | 2.010000e-01 |
| **men_percread_81-100** | 6.106000e-01 | 1.400000e-01 | 4.353 | 0.022 | 1.640000e-01 | 1.057000e+00 |
| **women_percnoed_0-30** | 2.431000e-01 | 5.700000e-02 | 4.270 | 0.024 | 6.200000e-02 | 4.240000e-01 |
| **women_percnoed_31-60** | 1.788000e-01 | 4.400000e-02 | 4.035 | 0.027 | 3.800000e-02 | 3.200000e-01 |
| **women_percnoed_81-100** | -2.092000e-01 | 5.900000e-02 | -3.555 | 0.038 | -3.960000e-01 | -2.200000e-02 |

Table 4.2: Significant Variables from the model

eventually obtain better-paying jobs.

The variable N_gch_voc has a positive coefficient of 0.0183, indicating that as the number of vocational training centers in the area increases, the incidence of child labor also increases. This result may be counterintuitive, as one would expect that vocational training centers would reduce child labor by providing more opportunities for children to obtain skills and eventually get better-paying jobs. It is possible that this result is due to other unobserved factors that affect the relationship between vocational training and child labor.

The variables women_percchild05_31-60 and women_percchild05_61-80 are both positively associated with the elimination of child labor, with p-values of $0.023$ and $0.031$, respectively. These variables represent the percentage of women between the ages of $31 - 60$ and $61 - 80$ in the area. It is possible that these women are more likely to prioritize education and other alternatives to child labor for their children.

The variable district_Bongouanou has a positive p-value of $0.5971$, indicating that child labor is more prevalent in this district compared to others. This result suggests that there may be specific factors unique to this district that contribute to the higher incidence of child labor, such as a lack of job opportunities or inadequate education infrastructure.

Overall, the results of this regression analysis suggest that increasing the number of kindergartens and the percentage of women in the population may be effective strategies for reducing child labor. However, the relationship between vocational training centers and child labor is not straightforward and requires further investigation. Additionally, addressing the specific factors that contribute to higher levels of child labor in certain districts may be necessary to effectively combat the issue. Also, several district variables were also found to be statistically significant, indicating that the district where a child resides has a significant impact on the incidence of child labor. For example, the district variable for Daoukro has a positive coefficient of 1.3422, indicating that child labor is more prevalent in this district compared to others. In contrast, the variable for Bocanda has a positive coefficient of 0.4486, indicating that child labor is less prevalent in this district compared to others.

## 4.2 Calculation of economic benefits

In order to estimate the economic benefits of eliminating child labor in Côte d'Ivoire, we employ the formula of equation (3.3) that takes into account several key parameters. These parameters, which have been carefully chosen to reflect the specific context of the study, are as follows:

- GDP Percentage: This parameter represents the proportion of the Gross Domestic Product (GDP) included in the calculation of the benefits. In our analysis, we set the value to $0.04$, which implies that $4\%$ of the GDP of Côte d'Ivoire saved by eliminating a child from child labor.

- Interest Rate: The interest rate plays a significant role in evaluating the present value of future benefits. For this study, we assume an interest rate of $7.1\%$, reflecting the prevailing economic conditions and discounting future benefits accordingly as of World Bank (2017).

- Standard of Living Wage and Under Standard of Living Wage: These parameters represent the wage differentials between the standard of living and the actual wages earned by child laborers. The value of SLW is set to $\$3458.05$, while USLW is set to $\$1537.03$, reflecting the wage disparity that exists in Côte d'Ivoire (Ministère de la Fonction Publique et de l'Emploi, 2008).

- Tax Variable: The tax variable in this calculation is determined by multiplying $0.015$ by $0.8$. The reason for using a tax rate of $1.5\%$ in this context is to calculate the minimum taxes earned by the government in terms of benefits. It is important to note that the actual tax rate may vary within a range of $1.5\%$ to $10\%$. By considering the lower end of the tax rate spectrum, this calculation provides a conservative estimate of the minimum tax revenue generated for the government based on $80\%$ of the gross income (GI) (Price Waterhouse Coopers, 2023).

- Lifespan of Labor: This parameter represents the number of years a child would spend in labor. In our analysis, we set the value to 20, based on available data and previous research on child labor in Côte d'Ivoire.

The graphical analysis of the benefits of eliminating child labor is presented in Figure 4.1. The x-axis represents the percentage of children eliminated from child labor, while the y-axis represents the corresponding economic benefits. The graph illustrates how the benefits change as the percentage of children in child labor increases. As the percentage of children out of child labor increases, the benefits increase, indicating the potential economic gains associated with the elimination of child labor. The graph provides a visual representation of the relationship between the reduction in child labor and the economic benefits derived from such a reduction.

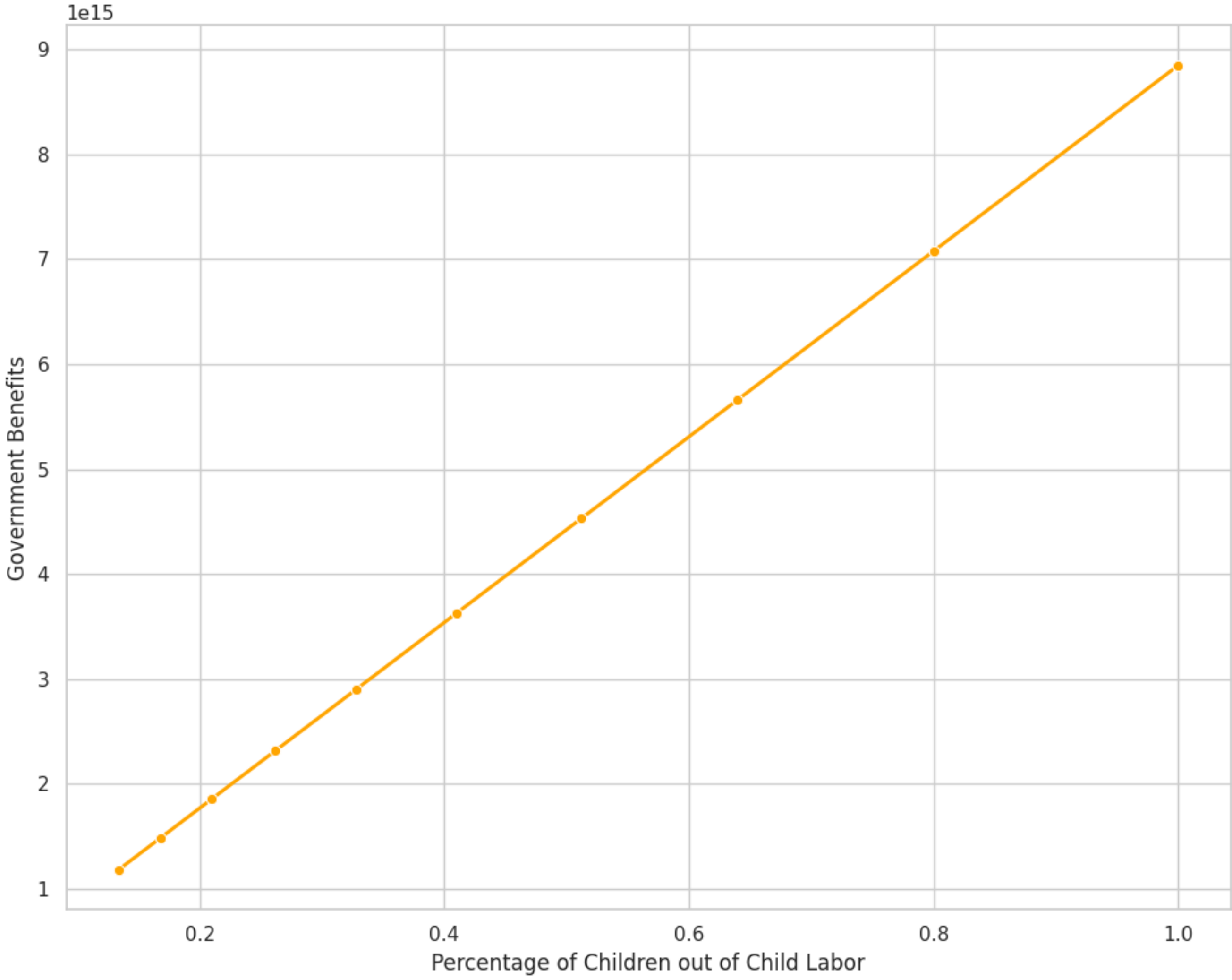


Figure 4.1: Graph of Percentage of children out of child labor against Government benefits

### 4.2.1 Findings

This section provides valuable insights into the factors influencing child labor rates and their potential implications for government benefits. Through a comprehensive analysis of various variables such as access to education, gender dynamics, and district-level effects, the research sheds light on actionable strategies that can be implemented to reduce child labor and enhance government benefits. By understanding the underlying causes and consequences of child labor, policymakers can develop targeted interventions that prioritize education, gender equality, and district-specific approaches. These findings offer a foundation for evidence-based policymaking, enabling governments to make informed decisions that foster economic growth, social development, and improved well-being for individuals and communities.

1. Increase in the number of kindergartens (kinderg d): By expanding the number of kindergartens, the government can provide access to early education and developmental opportunities for children. This can lead to better cognitive and social development, enhancing the human capital of the future workforce. As a result, the government can expect long-term benefits such as increased productivity, higher incomes, and a reduced reliance on child labor. Additionally, by addressing child labor, the government can improve its international reputation and attract foreign investments.

2. Increase in the number of vocational schools for girls (N gch voc): When the government focuses on increasing vocational education opportunities for girls, it can empower them with specialized skills and knowledge. This can lead to improved employment prospects and higher earning potential in the long run. By reducing the incidence of child labor among girls, the government can ensure that they have access to education and employment opportunities that align with their interests and abilities. This, in turn, can contribute to the overall economic growth and development of the country.

3. Increase in the percentage of women with children aged 5-60 months (women percchild05 31-60): By recognizing the positive correlation between the percentage of women with young children and child labor, the government can design policies and programs to support these women. Providing access to affordable childcare services, maternity leave, or income support can help alleviate financial burdens and enable mothers to balance their caregiving responsibilities with employment. As a result, more women can participate in the labor force, contributing to increased tax revenue and economic growth.

4. Increase in the percentage of women with children aged 5-60 months (women percchild05 61-80): This finding suggests that the government should continue or expand existing support systems or social programs that target women with children aged 5-60 months. These programs could include initiatives like early childhood education, healthcare services, nutrition programs, and income support. By investing in these areas, the government can improve the well-being of both women and children, reduce the need for child labor, and ensure better outcomes for future generations.

5. District-level effects on child labor: Analyzing the specific characteristics or circumstances in each district that influence child labor rates can help the government develop targeted

interventions. By understanding the factors contributing to child labor at the district level, the government can allocate resources and implement programs tailored to the unique needs of each area. This approach can maximize the impact of interventions, effectively reducing child labor and promoting socio-economic development in specific regions.

6. Effects of men's education levels: By recognizing the significant impact of men's education on child labor rates, the government can prioritize investments in education, especially for men. Increasing access to quality education at all levels, from primary to higher education, can equip men with the necessary skills for better employment opportunities. This can lead to increased household income, reduced poverty levels, and ultimately a decline in child labor rates. Additionally, educated men are more likely to support and advocate for their children's education, breaking the cycle of child labor in future generations.

7. Effects of women's literacy levels: Improving women's literacy levels can have multiple positive outcomes. Educated women are more likely to engage in income-generating activities, enhancing household incomes and reducing the need for child labor. Additionally, women's education has been linked to improved health outcomes, better family planning practices, and increased awareness of children's rights. These factors contribute to overall societal development and reduce the prevalence of child labor.

8. Effects of men's literacy levels: Similar to women's literacy levels, investing in men's literacy can have wide-ranging benefits. Increased literacy among men can enhance their employment prospects, leading to higher incomes and reduced reliance on child labor. Additionally, educated men can better support their families' education and advocate for children's rights. By promoting adult literacy programs, the government can empower men to actively participate in the workforce, positively impacting household well-being and reducing child labor rates.

In summary, addressing the factors identified in the research can help the government reduce child labor, promote economic development, and improve the well-being of individuals and families. By investing in education, gender equality, and targeted interventions, the government can reap long-term benefits, including increased tax revenue, improved international reputation, and sustainable economic growth.

# 5. Policy implications

Based on the results of the regression model and the estimated costs and benefits of eliminating child labor in Côte d'Ivoire, several policy implications and recommendations can be drawn.

Firstly, increasing the number of kindergartens in the area can help reduce the incidence of child labor. Governments and other stakeholders should invest in expanding early education and childcare programs to provide more opportunities for children to learn and develop skills that will enable them to eventually secure better-paying jobs.

Secondly, while vocational training centers are important in helping children acquire skills for better-paying jobs, the positive association between the number of such centers and child labor indicates that there may be other unobserved factors that contribute to this relationship. Governments and stakeholders should investigate these factors and take steps to address them to ensure that vocational training centers effectively reduce child labor.

Thirdly, the positive association between the percentage of women between the ages of $31 - 60$ and $61 - 80$ in the area and the elimination of child labor suggests that empowering women can have a positive impact on reducing child labor. This could be achieved through targeted policies and programs that support women's education and economic participation.

Finally, the estimated costs and benefits of eliminating child labor in Côte d'Ivoire highlight the economic gains that could be achieved through improved health outcomes and increased tax revenues from better job opportunities. Governments and stakeholders should prioritize policies and programs that promote the elimination of child labor and ensure that the costs of such programs are outweighed by their economic and social benefits.

In conclusion, the findings of this study suggest that a multi-faceted approach is needed to effectively eliminate child labor in Côte d'Ivoire. This includes investing in early education and childcare, addressing the underlying factors contributing to child labor, empowering women, and prioritizing policies and programs that promote the elimination of child labor. By taking these steps, Côte d'Ivoire can achieve significant economic and social benefits while improving the lives of children and families.

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# AppendixA. Appendix

## A.1 Variable description

This section provides a concise overview of the variables used in our regression analysis. It includes detailed descriptions of each variable, such as its definitions, measurement scales, and relevant units of measurement. Understanding these variables is crucial for interpreting the results and assessing the economic benefits associated with eliminating child labor. This section enhances the transparency and reproducibility of our study, enabling readers to gain a deeper understanding of the data and its implications for our regression model.

| | |
|---|---|
| **District name** | district |
| **Community name** | id_008_community_name |
| **Girls population** | pop_girls |
| **Boys population** | pop_boys |
| **Population children age 0-2** | pop_ch_0_2 |
| **Population children age 3-5** | pop_ch_3_5 |
| **Population children age 6-11** | pop_ch_6_11 |
| **Population children age 12-14** | pop_ch_12_14 |
| **Population children age 15-17** | pop_ch_15_17 |
| **Population girls age 0-2** | pop_girls_0_2 |
| **Population girls age 3-5** | pop_girls_3_5 |
| **Population girls age 6-11** | pop_girls_6_11 |
| **Population girls age 12-14** | pop_girls_12_14 |
| **Population girls age 15-17** | pop_girls_15_17 |
| **Population boys age 0-2** | pop_boys_0_2 |
| **Population boys age 3-5** | pop_boys_3_5 |
| **Population boys age 6-11** | pop_boys_6_11 |
| **Population boys age 12-14** | pop_boys_12_14 |
| **Population boys age 15-17** | pop_boys_15_17 |
| **girls enrolled in kindergarten** | N_gch_kinderg |
| **children enrolled junior high** | N_ch_jh |

Table A.1

| | |
|---|---|
| **girls enrolled in senior high** | N_gch_sh |
| **boys enrolled in senior high** | N_bch_sh |
| **children enrolled in senior high** | N_ch_sh |
| **girls enrolled vocational** | N_gch_voc |
| **boys enrolled vocational** | N_bch_voc |
| **children enrolled vocational** | N_ch_voc |
| **percent children birth certificates** | birth_cert |
| **kindergarten present** | kinderg |
| **number of kindergartens** | kinderg_n |
| **number of classrooms at kindergarten** | kinderg_c |
| **distance to nearest kindergarten** | kinderg_d |
| **primary present** | primary |
| **number of primary schools** | primary_n |
| **number of primary classrooms** | primary_c |
| **distance to nearest primary** | primary_d |
| **junior high present** | jhigh |
| **number of junior high schools** | jhigh_n |
| **number of junior high classrooms** | jhigh_c |
| **distance to nearest junior high** | jhigh_d |
| **senior high present** | shigh |
| **distance to nearest senior high** | shigh_d |
| **vocational school present** | voc |
| **number of vocational schools** | voc_n |
| **number of vocational classes** | voc_c |
| **distance to nearest vocational school** | voc_d |
| **primary healthcare centre present** | health_primary |
| **secondary healthcare facility present** | health_secondary |
| **distance to nearest secondary healthcare facility** | health_secondary_d |
| **access to electricity network** | electricity |
| **access to mobile network** | mobile |
| **access to internet** | internet |

| | |
|---|---|
| **community accessible all year round** | road3 |
| **ngo / organisation in community** | ngo |
| **license buying company in community** | buycompany |
| **cocoa farmer organisation in community** | cocoa_org |
| **number of female leader farmers** | flead |
| **number of male lead farmers** | mlead |
| **number of lead farmers** | lead |
| **training on gender issues conducted** | traingender |
| **number of leadership positions** | lead_pos |
| **number of leadership positions occupied by males** | lead_mpos |
| **number of leadership positions occupied by females** | lead_fpos |
| **Community Action Plan in community** | cap |
| **community generated revenue** | revenue |
| **revenue benefited children** | revenue_forchild |
| **Community Child Protection Committee in place** | ccpc |
| **percentage of women in leadership positions in community** | women_perc1 |
| **percentage of women deciding in farmer organizations in the community** | women_perc2 |
| **main education level of women in the community** | women_edu |
| **percentage of women that can read in the community** | women_percread |
| **percentage of women with no formal education in the community** | women_percnoed |
| **main education level of men in the community** | men_edu |
| **percentage of men that can read in the community** | men_percread |
| **percentage of men with no formal education in the community** | men_percnoed |
| **percentage of women consulting antinatal care in the community** | women_perccare |
| **percentage of women with children<5 in the community** | women_percchild05 |
| **percentage of women engaged in livelihood activities (apart from cocoa) in the community** | women_percliv |
| **Percentage of women owning land in the community** | women_percland |
| **Percentage of women owning and cultivating land in the community** | women_perclandcul |
| **Regulations to protect childern in the community** | childprot |
| **Remediation services for children in the community** | childrem |
| **Water point in the community** | waterpoint |

| | |
|---|---|
| **Minutes to the nearest water point in the community** | waterpoint_dist1 |
| **Distance (km) to the nearest water point in the community** | waterpoint_dist2 |
| **Households reduce meals per day** | reducemeal |
| **Cocoa farm size per farmer in the community (acres)** | cocoa_landsize |
| **Number of female cocoa farmers in the community** | cocoa_femalefarm |
| **Number of male cocoa farmers in the community** | cocoa_malefarm |
| **Number of cocoa farmers in the community** | cocoa_farm |
| **Cocoa production per farmer in the community (bags)** | cocoa_prod1 |
| **Cocoa production per farmer in the community (ton)** | cocoa_prod2 |
| **Cocoa production per year in the community (bags)** | cocoa_prod3 |
| **Cocoa production per year in the community (ton)** | cocoa_prod4 |
| **Extension services in the community** | extserv |
| **No. of females treained by ext. services in the community** | extserv_female |
| **No. of males treained by ext. services in the community** | extserv_male |
| **Farmers treained by ext. services in the community** | extserv_tot |
| **Farming inputs available in the community** | input_av |
| **Farming inputs affordable in the community** | input_af |
| **Adult casual work available in the community** | casualwork_av |
| **Farm labor cost per day** | casualwork_cost |
| **Agricultural services in the community** | agrserv |
| **Female children enrolled in Primary (No.)** | CED_N_gch_prim |
| **Male children enrolled in Primary (No.)** | CED_N_bch_prim |
| **Children enrolled in Primary (No.)** | CED_N_ch_prim |
| **Children from other comm. enrolled in Primary (No.)** | CED_N_ch_primotherc |
| **Female children enrolled in Primary 1 (No.)** | CED_N_gch_prim1 |
| **Male children enrolled in Primary 1 (No.)** | CED_N_bch_prim1 |
| **Children enrolled in Primary 1 (No.)** | CED_N_ch_prim1 |
| **Classrooms in Primary 1 (No.)** | CED_N_cl_prim1 |
| **Female children enrolled in Primary 2 (No.)** | CED_N_gch_prim2 |
| **Male children enrolled in Primary 2 (No.)** | CED_N_bch_prim2 |
| **Children enrolled in Primary 2 (No.)** | CED_N_ch_prim2 |

| | |
|---|---|
| **Classrooms in Primary 2 (No.)** | CED_N_cl_prim2 |
| **Female children enrolled in Primary 3 (No.)** | CED_N_gch_prim3 |
| **Male children enrolled in Primary 3 (No.)** | CED_N_bch_prim3 |
| **Children enrolled in Primary 3 (No.)** | CED_N_ch_prim3 |
| **Classrooms in Primary 3 (No.)** | CED_N_cl_prim3 |
| **Female children enrolled in Primary 4 (No.)** | CED_N_gch_prim4 |
| **Male children enrolled in Primary 4 (No.)** | CED_N_bch_prim4 |
| **Children enrolled in Primary 4 (No.)** | CED_N_ch_prim4 |
| **Classrooms in Primary 4 (No.)** | CED_N_cl_prim4 |
| **Female children enrolled in Primary 5 (No.)** | CED_N_gch_prim5 |
| **Male children enrolled in Primary 5 (No.)** | CED_N_bch_prim5 |
| **Children enrolled in Primary 5 (No.)** | CED_N_ch_prim5 |
| **Classrooms in Primary 5 (No.)** | CED_N_cl_prim5 |
| **Female children enrolled in Primary 6 (No.)** | CED_N_gch_prim6 |
| **Male children enrolled in Primary 6 (No.)** | CED_N_bch_prim6 |
| **Children enrolled in Primary 6 (No.)** | CED_N_ch_prim6 |
| **Classrooms in Primary 6 (No.)** | CED_N_cl_prim6 |
| **Children in Junior Secondary School (No.)** | CED_N_ch_js |
| **Teachers paid by the government (No.)** | CED_teacher |
| **Classrooms available for primary pupils (No.)** | CED_class_prim |
| **Female attendance rate in Primary 1** | CED_gattend_prim1 |
| **Male attendance rate in Primary 1** | CED_battend_prim1 |
| **Attendance rate in Primary 1** | CED_attend_prim1 |
| **Female attendance rate in Primary 6** | CED_gattend_prim6 |
| **Male attendance rate in Primary 6** | CED_battend_prim6 |
| **Attendance rate in Primary 6** | CED_attend_prim6 |
| **Female drop out rate in Primary 1** | CED_gdropout_prim1 |
| **Male drop out rate in Primary 1** | CED_bdropout_prim1 |
| **Drop out rate in Primary 1** | CED_dropout_prim1 |
| **Female drop out rate in Primary 6** | CED_gdropout_prim6 |
| **Male drop out rate in Primary 6** | CED_bdropout_prim6 |
| **Drop out rate in Primary 6** | CED_dropout_prim6 |
| **Pupil teacher ratio in Primary** | CED_ptratio_prim |
| **Toilet facilities at primary school** | CED_toilet_prim |
| **Assistance for out-of-school children in the community** | CED_outofsch |

| | |
|---|---|
| **Some children receive scholarship to attend Secondary school** | CED_scholarship |
| **Feeding programme at Primary school** | CED_feed_prim |
| **Classrooms in Primary (No.)** | CED_Ncl_prim |
| **girls enrolled in junior high** | N_gch_jh |
| **boys enrolled in junior high** | N_bch_jh |
| **boys enrolled in kindergarten** | N_bch_kinderg |
| **children enrolled in kindergarten** | N_ch_kinderg |
| **girls enrolled in primary** | N_gch_prim |
| **boys enrolled in primary** | N_bch_prim |
| **children enrolled in primary** | N_ch_prim |
| **Community code** | community_code |
| **Total population** | pop_tot |
| **Adult population** | pop_ad |
| **Child population** | pop_children |
| **Adult male population** | pop_admale |
| **Adult female population** | pop_adfemale |
| **Percentage of children in child labour** | lcommp_clab |

## A.2 Regression model with OLS Codes

This section contains the Python code used to generate the results used within the framework of this research.

```
# -*- coding: utf-8 -*-
"""Copie de AIMS_PROJECT(Child_Labor).ipynb

Automatically generated by Colaboratory.

Original file is located at
    https://colab.research.google.com/drive/1qNNX31Ap23ApOa8dnMbcsENS7jkfrF77
"""

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.feature_selection import mutual_info_regression

plt.style.use("seaborn-whitegrid")
plt.rc("figure", autolayout=True)
plt.rc(
    "axes",
    labelweight="bold",
    labelsize="large",
    titleweight="bold",
    titlesize=14,
    titlepad=10,
)

df = pd.read_csv("ivory_coast.csv", encoding='ISO-8859-1')

from sklearn.impute import KNNImputer

import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split, KFold
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

# from statsmodels.genmod.generalized_linear_model import GLM
# import statsmodels.api as sm
from sklearn.feature_selection import mutual_info_regression

from sklearn.linear_model import Ridge, Lasso



from scipy import stats

from yellowbrick.regressor import residuals_plot
```

```
from yellowbrick.regressor import prediction_error

from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, StandardScaler

from statsmodels.genmod.generalized_linear_model import GLM
import statsmodels.api as sm
from sklearn.impute import KNNImputer

from sklearn.metrics import mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer

df.head()
data = df.drop(['pcode_region', 'pcode_region.1', 'id_007_district', 'pcode_district', '
    id_008_community_name', 'community_code'], axis = 1)



def plot_continuous_distribution(data: pd.DataFrame = None, column: str = None, height:
    int = 8):
  for col in column:
    _ = sns.displot(data, x=col, kde=True, height=height, aspect=height/5).set(title=f'
        Distribution of {col}');

# def make_mi_scores(X, y):
# X = X.copy()
# for colname in X.select_dtypes(["object", "category"]):
# X[colname], _ = X[colname].factorize()
# # All discrete features should now have integer dtypes
# discrete_features = [pd.api.types.is_integer_dtype(t) for t in X.dtypes]
# mi_scores = mutual_info_regression(X, y, discrete_features=discrete_features,
    random_state=0)
# mi_scores_df = pd.DataFrame({"Feature": X.columns, "MI Score": mi_scores})
# mi_scores_df = mi_scores_df.sort_values(by="MI Score", ascending=False).reset_index(
    drop=True)
# return mi_scores_df

def make_mi_scores(X, y):
    X = X.copy()
    for colname in X.select_dtypes(["object", "category"]):
        X[colname], _ = X[colname].factorize()
    # All discrete features should now have integer dtypes
    discrete_features = [pd.api.types.is_integer_dtype(t) for t in X.dtypes]
    mi_scores = mutual_info_regression(X, y, discrete_features=discrete_features,
        random_state=0)
    mi_scores = pd.Series(mi_scores, name="MI Scores", index=X.columns)
    mi_scores = mi_scores.sort_values(ascending=False)
    return mi_scores

# def plot_mi_scores(scores):
# scores = scores.sort_values(ascending=True)
```

```
# width = np.arange(len(scores))
# ticks = list(scores.index)
# plt.barh(width, scores, color = 'black')
# plt.yticks(width, ticks)
# plt.title("Mutual Information Scores")

def plot_mi_scores(scores):
    scores = scores.sort_values(ascending=True)
    width = np.arange(len(scores))
    ticks = list(scores.index)
    plt.barh(width, scores, color='black')
    plt.yticks(width, ticks)
    plt.title("Mutual Information Scores")

    # Adjust y-axis visibility
    plt.gca().spines['left'].set_color('black') # Set y-axis color
    plt.gca().spines['left'].set_linewidth(1.5) # Set y-axis thickness

    # Add gridlines
    plt.grid(axis='x', linestyle='--', color='gray', linewidth=0.5)

    plt.show()

cat = []
num = []
for i in data.columns.tolist():
    if data[i].nunique() == 2:
        cat.append(i)
    else:
        num.append(i)

for i in cat:
    for j in range (len(data[i])):
        if data[i][j] == 1:
            data[i][j] = "Yes"
        if data[i][j] == 0:
            data[i][j] = "No"



X = data.loc[:,data.columns != 'lcommp_clab']
y = data['lcommp_clab']


# Separate numerical variables from the DataFrame
numeric_cols = X.select_dtypes(include=['int', 'float']).columns.tolist()
X_numeric = X[numeric_cols].copy()

# Create a Random Forest regressor
rf_regressor = RandomForestRegressor()

# Create an imputer with the Random Forest regressor
imputer = IterativeImputer(estimator=rf_regressor)
```

```
# Impute missing values in the numerical variables
X_numeric_imputed = imputer.fit_transform(X_numeric)

# Convert the imputed numerical variables back to a DataFrame
X_imputed = pd.DataFrame(X_numeric_imputed, columns=numeric_cols)
```

```
missing_val_count_by_column = (data.isnull().sum())
print(missing_val_count_by_column[missing_val_count_by_column > 0])

num_cols = data.select_dtypes(include=['int', 'float']).columns.tolist()
cat_cols = data.select_dtypes(include=["object"]).columns.tolist()

imputer = KNNImputer(n_neighbors=5)
data_num = pd.DataFrame(imputer.fit_transform(data[num_cols]), columns=num_cols)

cols = data_num.columns.tolist()
data[cols] = data_num[cols]
data = data.drop(['CED_outofsch'], axis= 1)

missing_val_count_by_column = (data.isnull().sum())
print(missing_val_count_by_column[missing_val_count_by_column > 0])
```

```
features = data.columns.tolist()
sns.relplot(
    x="value", y="lcommp_clab", col="variable", data=data.melt(id_vars="lcommp_clab",
        value_vars=features[26:28]), facet_kws=dict(sharex=False),
);

plot_continuous_distribution(data, features[26:28], height= 8)

X = data.copy()
y = X.pop('lcommp_clab')

mi_scores = make_mi_scores(X, y)
mi_scores.to_csv("scores.csv")

selected_features = mi_scores.loc[mi_scores["MI Score"] != 0.0, "Feature"].tolist()

selected_features.append('lcommp_clab')

print(mi_scores.head(20))

plt.figure(dpi=100, figsize=(10, 9))
plot_mi_scores(mi_scores.head(25))
# plot_mi_scores(mi_scores.tail(20)) # uncomment to see bottom 20
```

```
def plot_categorical_distribution(df, x_col, count_column, height=8, aspect=2):
      _ = sns.catplot(data=df, x=x_col, y=count_column, kind='bar', estimator=sum, height=
          height, aspect=aspect, ci=None)
      _.set(title=f'Distribution of {x_col}')
      _.set_axis_labels(x_col, "Count of Child labor percentage")
plot_categorical_distribution(df, 'region', 'lcommp_clab')

def plot_categorical_distribution(data, column, height = 8, aspect = 2):
  for col in column:
    _ = sns.catplot(data=data, x=col, kind='count', height=height, aspect=aspect).set(
        title=f'Distribution of {col}');

# plot_categorical_distribution(data, features[160:164], height = 8, aspect = 2)
sns.catplot(data=data, x='CED_feed_prim', kind='count', height=8, aspect=2, palette='Set1
    ');
plt.xlabel('Feeding Program at Primary School')
plt.ylabel('Count of regions with Feeding programs')

sns.catplot(x="women_percchild05", y="lcommp_clab", data=data, kind="boxen");

feature = "N_ch_kinderg"

sns.lmplot(
    x=feature, y="lcommp_clab", hue="kinderg", col="kinderg",
    data=df, scatter_kws={"edgecolor": 'w'}, col_wrap=5, height=6,
);

selected_features.insert(0, 'lcommp_clab')

selected_dataset = data[selected_features[0:22]]##greater than 0.05
selected_dataset.head()

"""### LINEAR REGRESSION"""

# put the categorical variables into category type
categorical_columns = list(selected_dataset.dtypes[selected_dataset.dtypes == 'O'].index.
    values)

for column in categorical_columns:
    selected_dataset[column] = selected_dataset[column].astype('category')

num_cols = selected_dataset.select_dtypes(include=['int', 'float']).columns.tolist()
cat_cols = selected_dataset.select_dtypes(include=["category"]).columns.tolist()

num_cols.remove('lcommp_clab')

X = selected_dataset.loc[:,selected_dataset.columns != 'lcommp_clab']
y = selected_dataset['lcommp_clab']

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.25,random_state=42)

X_train.shape, X_test.shape, y_train.shape, y_test.shape

# Preprocess data to create one-hot encoded features for categorical variables
```

```
X_num = X_train[num_cols]
X_cat = pd.get_dummies(X_train[cat_cols])
X = pd.concat([X_num, X_cat], axis=1)
y = y_train

# Fit an OLS model to the preprocessed data
X = sm.add_constant(X)
model = sm.OLS(y, X)
results = model.fit()

# Print a summary of the fitted OLS model
print(results.summary())



# Select variables with p-values less than 0.05
significant_vars = results.pvalues[results.pvalues < 0.05].index.tolist()

# Print the list of significant variables
m = pd.DataFrame(significant_vars)
m.head(20)

# Fit an OLS model
model = sm.OLS(y, X)
results = model.fit()

# Filter the rows based on p-values
summary = results.summary()
summary_df = pd.read_html(summary.tables[1].as_html(), header=0, index_col=0)[0]
filtered_summary_df = summary_df[summary_df['P>|t|'] < 0.05]

# Export filtered summary table to a LaTeX file
with open('filtered_summary.tex', 'w') as f:
    f.write(filtered_summary_df.to_latex())

summary_df = pd.read_html(results.summary().tables[1].as_html(), header=0, index_col=0)
    [0]
summary_df.to_csv('summary.csv')

filtered_summary_df.head(200)
```

Listing A.1: Model Python Code

## A.3 Benefits Codes

```
# -*- coding: utf-8 -*-
"""benefits.ipynb

Automatically generated by Colaboratory.

Original file is located at
    https://colab.research.google.com/drive/1RXDAFzJf5XX_tkXQ9-uw1Us-DvrOnm9a
"""

import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

percentage_child_labor = 1
gdp_percentage = 0.04
rate = 0.071 ##interest rate
slw = 3458.05
uslw = 1537.03
t = 0.015 * 0.8
lifespan_labor = 58
gdp = 70.39 * 10**9
num_children = 1400000

# Simulation parameters
simulation_duration = 10 # Number of years
initial_child_labor_percentage = 1 # Initial percentage of child labor
reduction_rate = 0.2 # Rate at which child labor reduces per year

# Initialize lists to store simulation data
years = np.arange(simulation_duration)
child_labor_percentages = [initial_child_labor_percentage]

# Simulate child labor rates over time
for year in range(1, simulation_duration):
    previous_percentage = child_labor_percentages[year - 1]
    current_percentage = previous_percentage - (previous_percentage * reduction_rate)
    child_labor_percentages.append(current_percentage)

def future_earnings(rate, lifespan_labor):
    sum= 0
    for i in range(lifespan_labor+1):
        sum += 1/(1+rate)**i
    return sum

def calculate_benefits(percentage_child_labor, num_children, gdp_percentage, gdp, slw,
    uslw, t, rate, lifespan_labor):
    health_benefits = percentage_child_labor * num_children *(gdp_percentage * gdp + (slw
        - uslw) * t ) * future_earnings(rate, lifespan_labor)
    return health_benefits * 0.053####inflation rate is 5.3%

sns.set(style="whitegrid") # Set seaborn style
```

```
plt.figure(figsize=(10, 8))

# Plot the data using sns.lineplot
sns.lineplot(x=child_labor_percentages, y=y_values, marker='o', linewidth=2,color = '
    orange')

# Uncomment the following line if you have a second dataset to plot
# sns.lineplot(x=y_values_1, y=child_labor_percentages, marker='s', linewidth=2)

# Set labels and title
plt.ylabel("Government Benefits")
plt.xlabel("Percentage of Children out of Child Labor")
# plt.title("")

plt.tight_layout() # Adjust spacing and margins

plt.show()
```

Listing A.2: benefits Python Code