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# Economic and Financial Crime in the Forestry Industry – Developed vs. Developing Countries

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## Abstract

Wood is one of the most important natural resources, used in construction and fencing, art (artworks and musical instruments), household uses (utensils and hand tools), wooden toys, furniture, shipbuilding, fuel, and stationary. Therefore, deforestation is an indispensable process to our society. However, deforestation does not have to mean smaller forestland, as it should be accompanied by afforestation. But this does not happen, partially due to illegal deforestation, that raises the deforestation level much higher than the sustainable one, and partially due to laws that permit legal deforestation to be above the durable limit, obviously for economic and political reasons The aim of this paper is to study the differences in the influence that economic and financial crimes (corruption, shadow economy, and money laundering) have on the rate of deforestation in developing versus developed countries. Recent data (from 2012 to 2020) is used for 185 countries from all over the world, in order to obtain updated and relevant results. The practical use of the findings is given by their relevance in finding efficient, adapted, and effective solutions for unsustainable deforestation (legal or not), for pollution, and for a cleaner air and environment, and for a better understanding of this phenomenon, by addressing it differently according to the level of development of a country. Also, this research is an attempt to raise awareness upon illegal deforestation and corruption. The regressions applied to the database show that both developed and developing countries present a direct connection between economic and financial crime and the level of deforestation, but in developed countries the influence of economic and financial crime on deforestation is lower. Therefore, the focus in reducing the deforestation by reducing the economic and financial crimes rate should be on developing countries, where the levels of corruption, shadow economy, and money-laundering are higher, and so is the deforestation rate.

**Keywords:** economic and financial crime, corruption, shadow economy, money laundering, developed countries, developing countries, GDP, deforestation, forest industry.

**Jel codes:** D73, Q01, Q23

## 1. Introduction

As presented in an earlier paper (Cozma, Achim, & Safta, 2022), besides the energetic, financial, and health crises, we also face, for a long period of time, an environmental crisis. The rapid and exponential development of technology and the growing population are the principal general causes of pollution, the most dangerous enemy to our health, wellbeing, and time on Earth. As for the specific causes, Ritchie & Roser (2016) show that energy use is the number one greenhouse gas emitter, with the iron and steel industry, road transport, and residential buildings being the biggest consumers. The cement industry is the first in the top of industries that emit greenhouse gases, just as the waste on the landfills is in the waste emitters rank. Livestock and manure are the biggest emitter in the Agricultural, Forestry, and Land Use sector, while deforestation places itself 4th, with a 2.2% from the total global greenhouse gas emissions on Earth.

However, even if it does not seem much, we must not forget that the real level of deforestation is unknown, as a great part of it is illegal and hidden. Also, we must also take into account that trees, along with other plans, are the only machines in our ecosystem that can produce oxygen by consuming the carbon dioxide. Deforestation is an important cause of global greenhouse gas emissions, and total forestland is shrinking and shrinking, while trees are the only natural solution to reduce them.

Wood is one of the most important natural resources, used in construction and fencing, art (artworks and musical instruments), household uses (utensils and hand tools), wooden toys, furniture, shipbuilding, fuel, and stationary. Therefore, deforestation is an indispensable process to our society. However, deforestation does not have to mean smaller forestland, as it should be accompanied by afforestation. But this does not happen, partially due to illegal deforestation, that raises the deforestation level much higher than the sustainable one, and partially due to laws that permit legal deforestation to be above the durable limit, obviously for economic and political reasons.

Now, 38% of the habitable land on Earth is forest. But 10.000 years ago, forests represented 57%. 50.000 years ago, 55%. In 1700, 52%. In 1800, 50%. In 1900, 48%. In 1950, 44%. Hence, in the last 120 years, we lost 10 percentual points, according to Ritchie & Roser (2021). This is a disturbing rate, as only in the last 30 years we lost 420 million hectares of forestland. The Amazonian rainforest was reduced by 17% only in the past 50 years. Besides the obvious practical uses of wood, trees now tie up almost 50% of the carbon stored on land. By shrinking the timberland, its capacity to reduce pollution will continue to decrease dramatically. It is important to mention that this excess of carbon causes climate changes, which consequences are multiple and well-known. However, special attention must be given to wildfires, which cause a vicious circle: less trees, higher temperature, more wildfires, less trees.

Forests are cut down not only to obtain wood, but for using the land for other purposes: farming, drilling, grazing of livestock, mining, urbanization (Nunez, 2021). Because the demand exceeds the legal supply of wood, illegal practices appear. Corruption at the high levels, with politicians that create interpretable laws, is a white-collar crime, but on the field, criminals and corrupt forest workers are often violent with the activists and with honest forest workers, resulting in serious verbal and physical aggressions, and even murders, as it happens in Romania.

The aim of this paper is to study the differences in the influence that economic and financial crimes (corruption, shadow economy, and money laundering) have on the rate of deforestation in developing versus developed countries. Recent data (from 2012 to 2020) is used for 185 countries from all over the world, in order to obtain updated and relevant results. The practical use of the findings is given by their relevance in finding efficient, adapted, and effective solutions for unsustainable deforestation (legal or not), for pollution, and for a cleaner air and environment, and for a better understanding of this phenomenon, by addressing it differently according to the level of development of a country. Also, this research is an attempt to raise awareness upon illegal deforestation and corruption.

Further on, chapter 2 of this paper presents a summary of the most relevant research in terms of economic and financial crime in the forest industry, which is actually not much. The next chapter presents the methodology, with descriptions of the variables used, the reasons for choosing them, and the statistical procedures applied. The findings of this study are reveled in chapter 4, by interpreting the statistical results from an economical point of view. The final part includes the conclusions of these findings, solutions proposed, limitations of the research, and future work.

## 2. Literature Review

There are three main types of economic and financial crime, as Achim and Borlea (2020) present: corruption, shadow economy and money-laundering. Corruption refers to the illegal use of public resources for personal gain. Shadow economy sums up all the activities that are not taken into consideration by legal norms and official statistics. Finally, money-laundering refers to the process of disguising money from illegal activities through fraudulent procedures in order to give them a legal appearance.

The previous academic research on the topic of economic and financial crime in relation to the level of deforestation has a very shy presence, as Table 1 shows:

**Table 1.** Academic research on deforestation in respect with economic and financial crime - number of results adjusted by keywords and relevance

| **Keywords** | **Web of Science database** | **ACM Digital Library** | **Science Direct** | **Emerald Insight** | **IEEE Transactions** | **Springer-Link Journals** |
|---|---|---|---|---|---|---|
| *Corruption, deforestation* | 140 results | 20 results | 24 results | 1 result | 0 results | 391 results |
| *Shadow economy, deforestation* | 6 results | 153 results | 0 results | 0 results | 0 results | 234 results |
| *Money-laundering, deforestation* | 6 results | 54 results | 3 results | 0 results | 0 results | 31 results |
| *Economic crime, deforestation* | 18 results | 5 results | 6 results | 0 results | 0 results | 215 results |

**Source:** Own processing

From these studies, many of them focus on qualitative, descriptive research methods, and the few ones that use quantitative, statistical methods are based on old data (most recent is from 22 years ago), with results that might not correspond to the present state. However, when it comes to deforestation, corruption is the criminal category that is most frequently highlighted. In order to support the variables chosen for the current research, the academic studies are further categorized by subtopic, along with discussions of the primary findings.

*2.1 Deforestation and Corruption*

Regarding deforestation, corruption is the economic and financial crime that is most frequently mentioned and obvious. But only 52 out of the 140 articles on corruption and deforestation that Web of Science has indexed are thought to have an economic or financial perspective.

Many articles exclusively address tropical forests and do not include a worldwide viewpoint. It is mostly descriptively explained how institutions, communities, and states play a part in land use, decentralization, property rights, laws, effects, and the value of conservation. Trade, the effectiveness of the political system (democracy), and GDP per capita (economic growth, environmental Kuznets' curve) may all be clearly detected, but from different sources.

The results of utilizing VOSviewer to find the most frequently used terms in the papers indexed by Web of Science, the most pertinent academic literature database, are shown in Figure 1.

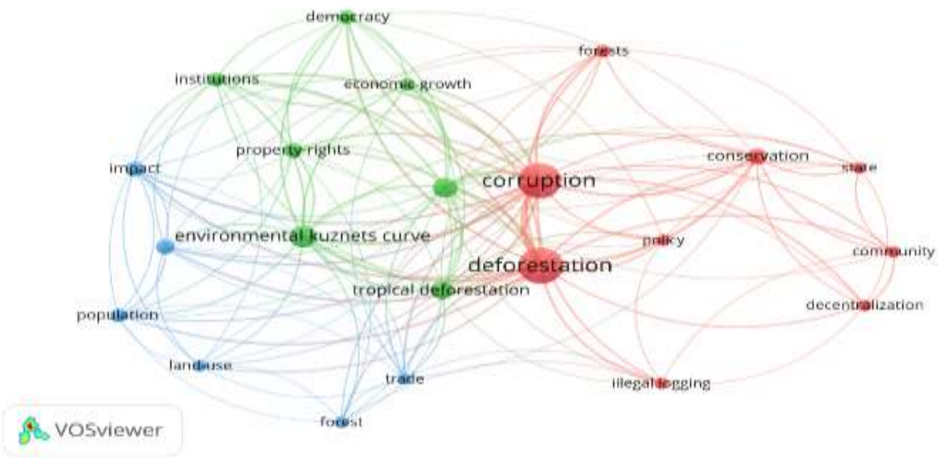


**Figure 1.** Bibliometric analysis of co-occurrence of "corruption" and "deforestation" as keywords in publications.

**Source:** Own processing using VOSviewer

Islam and Sato (2012) found that illicit logging and land conversion cause the forest degradation, in their study on deforestation in Bangladesh. By controlling a few biophysical and anthropogenic variables, *corruption* levels, according to Barret, Gibson, Hoffman, and McCubbins (2006), have little explanatory value in connection to the exploitation of natural resources. But at least when it comes to deforestation, there are several studies that refute them. According to Amacher, Ollikainen, and Koskela (2012), harvesters bribe logging inspectors to avoid paying fines for unlawful logging. This is the most common type of corruption in the forestry business. Additionally, Ali and Nyborg (2010) examine how forest agents participate in the "alternative system" in order to perform official responsibilities. According to Shanee and Shanee (2016), corruption is a significant catalyzer of land trafficking. Decentralization and corruption are taken into consideration by Ji, Ranjan, and Truong (2018) when identifying the elements that significantly and favorably affect unlawful deforestation. Additionally, Sundstrom (2013) examines the conflict between resource users' faith in inspectors and their claim that corrupt practices lessen those inspectors' credibility. But the line of bribery extends far further, all the way to politicians. Sundstrom (2016) draws the conclusion that bribery is the most potent inducement for illegal deforestation following an excellent examination of the literature. The excessive deforestation and low land production are explained by Bulte, Damania, and Lopez (2007) as a result of affluent farmers bribing political donors and government officials for subsidies. Pailler (2018) makes an intriguing discovery: there are "electoral deforestation cycles" in the Amazon, which means that deforestation rates rise during election years. The phenomenon is linked to campaign finance and, consequently, corruption, and it is hypothesized that "weak institutional constraints facilitate electoral manipulation of forest resources". Corruption, in the opinion of Sodhi (2008), is a major obstacle to tropical conservation. According to Indarto, Kaneko, and Kawata (2015), Indonesian logging licenses have a negligible correlation to deforestation, which raises questions about how much forest is being illegally exploited there. Another study, conducted by Ali, Benjaminsen, Hammad, and Dick (2005), focuses on the deforestation in Pakistan's Western Himalayas and the Basho Valley. The study's findings are in conflict with theories linking population growth and deforestation, but they support the significant role that illegal harvesting and poor management have in the loss of forest cover. The REDD (Reducing Emissions from Deforestation and Degradation) initiative, which intends to encourage poor nations to take significant action in reducing greenhouse gas emissions, is discussed by Brown (2010) as having the potential to be jeopardized by corruption. Additionally, Sheng, Han, Zhou, and Miao (2016) demonstrate through the use of panel data from 2010 to 2013 for 11 partner countries in the UN-REDD Programme that one of the main obstacles to the efficacy of REDD programs is, in fact, corruption. There is also research by Wehkamp, Aquino, Fuss, and Reed (2015) that discusses the significance of institutional and policy forces recognized by African policy makers as drivers for deforestation. This study is important in light of potential policy solutions proposed in the REDD+ initiative.

Mendes and Porto Junior (2012) demonstrate that the *economic growth* is statistically significant in a direct relationship to the degree of illicit deforestation by focusing primarily on Brazilian towns in the Amazon area. Similar conclusions were reached by Wolfersberger, Delacote, and Garcia (2015): "economic development and institutions play a significant role in long-term deforestation". Furthermore, according to Ewers (2006), "there is a strong interaction between forest cover and economic development that determines rates of forest change among nations". According to Laurance's research, low-income nations see the greatest loss of forests and are "plagued by endemic corruption" (2007). However, according to Bakehe (2020), the maintenance of forest cover is negatively correlated with GDP per capita.

In a previous publication, Cozma, Cotoc, Vaidean, and Achim (2021) wrote a similar article in which they attempted to determine the statistically significant determinants of corruption in the forestry industry. They came to the conclusion that democratic governance quality, wood export share, press freedom, and culture are significant factors that should be taken into account when choosing the appropriate countermeasures that aim to reduce illegal deforestation.

*2.2 Deforestation and Shadow-Economy*

Even though there are only six papers on the subject of deforestation and the shadow economy included in the Web of Science database, certain themes may be recognized: the issues of agriculture and the environment are discussed in relation to both the shadow economy and corruption, as was described in the preceding section. However, especially when it comes to the frontier boundaries, corruption and illicit logging are strongly related to the shadow economy.

In addition to the article by Cozma, Cotoc, Vaidean & Achim (2021), which found a significant and favorable relationship between the amount of the shadow economy and the rate of deforestation, there is another study by Mahanty (2019), which discusses two points of connection: land transactions and border checkpoints, both through state officials, that show the relationship and practices of timber trade across the border of Cambodia and Vietnam. But according to research by Pattanayak, Sills, and Kramer (2004), "the number of trips taken by households depends on the shadow price of fuelwood collection or the travel cost, which is endogenous", the behavior of users of fuelwood appears to be economically sensible. At the global scale, Pollini (2011) demonstrates how the control of the hidden natural resource economy leads to the failure of international projects in the shadow states. There is no obvious deforestation, according to Alexandrowicz (2017), who conducted study on the fauna and flora of the Ociemny Stream valley in the Pieniny Mountains. This is because there are no plans for economic growth in the area. As a result, economic expansion is once again shown to be the primary cause of forest degradation. Regarding the suggested remedy, Nazarova, Martin, and Giuliani (2020) advocate a detection strategy based on a high cloud detection system for keeping an eye on the forestland and stopping illegal logging.

*2.3 Deforestation and Money-Laundering*

Money-laundering and deforestation are only mentioned in 6 papers listed in the Web of Science database, with a similarly limited presence in the specialized literature as the prior subtopic. The relationship between drug trafficking and deforestation is the subject of three of the six papers included in the Web of Science database that all feature Jennifer A. Devine as the first author and were all published in 2020 or 2021. Additionally, she is the fifth co-author on a fourth one. Devine, Wrathall, Currit, Tellman, and Langarica (2020) identify the problem of "narco-ganaderia" or "narco-cattle ranching" as the deforestation carried out by drug traffickers and assert that "drug policy is inextricably linked to conservation policy" as the starting point of their research. Devine, Currit, Reygadas, Liler, and Allen (2020), who published the second article, provide a clearer explanation of the scope: to illegally ranch cattle, as a method of money-laundering, territorial control, and drug smuggling. The majority of the destruction in Guatemala's Maya Biosphere Reserve appears to be the result of illicit cattle grazing. Additionally, they claim that the drug traffickers are to accountable for the forest destruction, not the farmers who unlawfully occupy the reserve. In a third article, Devine et al. (2021) underline the notion that the worldwide cocaine trade is mostly to blame for deforestation and that drug traffickers use the extractive industries as a means of money laundering in order to gain control of regions along the supply chain. The acceleration of the conversion of natural resources into commodities is the environmental impact of narcotrafficking. The fourth article by Tellman et al. (2020) uses a quantitative method to examine how drug trafficking affects illicit land deals, territorial control, and money laundering, as well as how much forest is lost when grazing or agricultural land is converted to other uses. According to the authors, Central America's forest degradation is accelerated by drug trafficking since these places are isolated and have significant cultural and environmental importance. In addition, Fearnside (2008) identifies land speculation, money laundering, and drug trafficking as further macroeconomic shifts that contribute to the spread of deforestation. These include fluctuations in commodity prices and significant subsidies. Another study on this subject was published by Ozinga and Mowat (2012), who evaluate the laws and regulations pertaining to deforestation, illicit wood exports, the involvement of NGOs, and the efficacy of various programs.

As a result, there is a two-way relationship between deforestation and money-laundering: one is to convert forestland into a site for the manufacturing of narcotics, and the other is to integrate the proceeds of illicit logging into the formal economy.

*2.4 Deforestion and Economic and Financial Crime*

With three times as many publications on this topic, the broader definition of economic and financial crime—which encompasses all the subtypes previously examined (corruption, shadow economy, and money-laundering)—now emphasizes a number of fresh issues, including green criminology, minerals, and financing options like REDD++ for projects that aim to improve the environment (gold, mercury). However, the emphasis on tropical forests, the economic component, and agricultural principles are all rediscussed. The great majority of these articles tackle *environmental* problems and difficulties in general as well as deforestation specifically.

As Luis Carpio-Dominguez (2021) concentrates his research on the criminal gangs in the natural protected areas of Mexico, the impact of drug trafficking on the environment is once again brought up. Through semi-structured interviews, he learns that these plots of land serve as critical control sites for the cultivation and mobilization of narcotics in the drug trafficking scene.

Barroso and Campos Mello (2020) brigh up the subject of "environmental crimes" in the context of the Amazonian ecology, which has been devastated by unauthorized mining, illicit logging, and land grabbing. The authors examine models of forest exploitation and come to the conclusion that they have few economic and social effects. Lynch, Long, Barrett, and Stretesky (2013) also wrote a paper on "green crimes," with one of the key findings being that political economy should be the main area of concentration in order to address green damages. The researchers also examine the connection between capitalism and environmental problems. Latif and Munir (2017) examine this system of economic reliance and demonstrate how many people's lives are based on forests.

Drapenzo and Shelestukov (2019) analyze the impact the Kemerovo State University has on reducing economic and ecological crime by fusing the efforts of executive authorities, public organizations, and active citizens with their own, successfully recognizing and preventing ecological and economic offenses. They do this by focusing only on one region, namely the Kemerovo Oblast. Another study, conducted by Papuc, Pintilii, Andronache, Peptenatu, and Dobrea (2015), focuses on changes to Romania's forestland between 2000 and 2012. It reveals a connection between the rising deforestation rate, the expansion of industries that use wood as a raw material, the rise in forest crime, and the expansion of the timber export industry.

In her research, Sullivan (2013) focuses on the Brazilian area of Mato Grosso do Sul, where forests are cleared for agricultural crops and cattle ranches. Activists for Guarani land believe that issues like high crime rates and malnutrition are related to the relocation. The author investigates the ethnic borders of the locals due to their strong sense of territoriality, which frequently leads to violent counter-mobilization. Additionally, Gunes and Elvan (2005) undertook a research to look into the illegal logging practices in Turkey. Their findings stem from the political, cultural, and economic systems in Turkey. According to Villar and Schaeffer (2019), the primary driver of deforestation in the Afro-Columbian Pacific States is unrestricted mining. Pozmogov, Kallagov, Tedeeva, Kuchieva, and Gergaeva (2019) analyze the problems in the North Caucasus Federal District and cite inefficient water usage, resource depletion, deforestation, and the loss of numerous animal and plant species as the main reasons of the current environmental condition. They also discuss the urgent need for a fresh approach to ecological thinking that is suitable for the present problems. Moving on to Sub-Saharan Africa, Cavanagh, Vedeld, and Traedal (2015) provide a critical analysis of the "black side" of the REDD+ initiative, focusing on "its potential for leakage effects on adjacent jurisdictions and deleterious implications for forest-dependent communities". According to Minten, Sander, and Stifel (2013), granting permits for the exploitation of wood is the preferred approach of managing natural resources in Madagascar. The researchers used a survey information from 178 charcoal sellers, those with stronger ties to the government "have grater access to the rents that stem from charcoal regulation". The authors suggest creating and updating these license policies as a fix. According to Laing (2019), Guyana's mining sector contributed to deforestation as well as other social issues like prostitution, criminality, and human trafficking. Santibanez and Santibanez (2007) explain how tropical rainforests are cleared using fire to open lands for pastures and crops, focusing their research on the ecosystems of Latin America.

More generally, a conceptual framework presented by Tellman, Magliocca, Turner, and Verburg (2020) illustrates the significant impact such unlawful activities have on land change by connecting illicit activities to land uses. According to Koren and Butler (2006), the built environment contributes to the continued expansion of deforestation, particularly in emerging nations and is mostly done "to serve wealthy metropolitan population." The built environment's influence on health and crime levels are also taken into account. The interdependence and intricacy of the built environment, security, ecology, and human health are highlighted in this study.

Chen, Powers, de Carvalho, and Mora (2015) talk about one intriguing subtopic: the drawbacks of hydroelectric dams. The authors, who are concentrating on Amazon, acknowledge all of its advantages but also provide some information on the disruption of the natural ecological dynamics that resulted in considerable tree loss. The authors also discovered that deforestation and forest degradation had comparable territorial patterns in the areas around the dams.

As is evident, the great majority of studies concentrate on specific geographical areas, employ qualitative research techniques, and even the quantitative studies use very outdated data bases. The most current dataset, which is an outlier because the majority of them halt in 2000, ends in 2015. The association between deforestation and economic and financial crime, as well as its drivers, calls for a quantitative and current analysis. No effective remedy or policy can be created without an updated fact-based view on this problem.

Due to the inadequate level of information at this point, illegal deforestation is not at all a popular subject in academia. However, there has been a significant loss of forestland in the previous 30 years and climate change is as serious as it can be, making it imperative to do current, fact-based research on deforestation.

In an earlier study, we proved that economic and financial crime is directly and positevely linked with deforestation (Cozma, Achim, & Safta, 2022). The current study intends to provide answers to the following research question: Does financial and economic crime have a higher impact on the rate of deforestation in developing countries than in the developed ones?

Hypothesis: Economic and financial crime has a higher impact on the rate of deforestation in developing countries.

**3. Data & Methodology**

Secondary data regarding corruption, shadow economy, money-laundering, deforestation, wealth of a country, and environmental vitality has been analyzed for 185 countries between 2012 and 2021. The selection of the countries is based on the available data and the relief, especially the amount of forestland. Appendix A includes the whole list of countries, as well as the classification “developed” vs. “developing”. The most recent data has been used in order to achieve accuracy, 2012 being the year when a lot of changes in the methodologies of calculating indicators have occurred.

Net Forest Conversion Rate (NFCR) represents the dependent variable, and it is constructed by dividing the different in Forestland (FL) from two consecutive years to the Forestland in the previous year. NFCR takes negative values when the forestland decreased due to a greater deforestation than afforestation, and positive values when the forestland increased due to a greater afforestation than deforestation.

As independent variables, three variables that illustrated the types of economic and financial crime are used: corruption, measured with the Corruption Perception Index (CPI), shadow-economy (SE), as calculated by Medina & Schneider (2019) and Schneider (2022), and money-laundering, using the Anti-Money-Laundering Index (AML), calculated by Basel Institute on Governance.

As control variables, GDP per capita (GDP) and Environment Performance Index (EPI) have been used, in order to suppress the differences in living standards and ecosystem vitality, as discussed in the literature review chapter.

The description of the variables and data used is presented in Table 2:

**Table 2.** Description of variables

| **Variables** | **Way of estimations** | **Description** | **Unit measure** | **Source** |
|---|---|---|---|---|
| **Dependent variable** | | | | |
| *Deforestation* | Net forest conversion rate (NFCR) | The percentage of forestland added or subtracted in a country, in a year; own formula: NFCR (t) = [FL(t) – FL (t-1)]*100 / FL(t-1) with t representing the year and t-1 representing the previous year; FL represents the total forestland in a country, measured in 1000 ha | % | Food and Agricultural Organization (FAO) (2020) |
| **Independent variable** | | | | |
| *Economic and financial crime* | Corruption Perception Index (CPI) | The level of perceived corruption in a country | a scale from 0 (extremely corrupt) to 100 (not corrupt at all) | Transparency International (2021) |
| | Shadow economy (SE) | Shadow economy as percentage from the total official GDP in a country | % | Medina & Schneider (2022) |
| | Anti-money-laundering Index (AML) | A country's vulnerability to money-laundering and its capacities to counter it | a scale from 0 (not vulnerable at all) to 10 (extremely vulnerable) | Basel Institute on Governance (2021) |
| **Control variables** | | | | |
| Wealth of the country | Gross domestic product per capita (GDP) | A country's GDP per capita | Thousands of US dollars ($) | World Bank (2021) |
| Environment | Environmental Performance Index (EPI) | It measures the environmental health and ecosystem vitality of a country. | a scale from 0 (least environmentally friendly) - 100 (most environmentally friendly) | Yale Center for Environmental Law & Policy (2022) |

**Source:** Own processing

Because there is no available data on illegal deforestation at the international level, the most accurate data for unsustainable forest management is the relative change in woodland. For this, data on the total surface of forestland has been used, as published by Food and Agricultural Organization (FAO). It considers every piece of land larger than 0.5 hectares, with trees taller than 5 meters, and a canopy cover higher than 10%. The measurement excludes the land that is under urban or agricultural use, as well as the land used for management and restauration of environmental function. The Net Forest Conversion Rate (NFC) is a relative measurement of the change in forestland, calculated as the difference in forestland between two consecutive years, divided by the forestland in the previous year.

Because there is no precise measurement for the degree of corruption either, the Corruption Perception Index (CPI) is the most widely used, complex, and reliable indicator for it. It has been published yearly by Transparency International since 1995. Expert assessments and public opinion surveys are used to rank nations based on how corrupt they are thought to be. The scale used spans from 0 to 100, with 100 being the least perceived corruption and 0 representing the greatest. High CPI ratings essentially indicate minimal levels of corruption.

The databases created by Medina & Schneider (2019) and Schneider (2022) are the most trustworthy sources of data on the shadow economy (SE). The SE is expressed as a percentage of the real GDP. Their database includes 157 nations and covers the years 1991 to 2017, respectively 36 countries between the years 2003-2022. The multiple indicator-multiple trigger (MIMIC) approach was applied to its computation. Its inability to be fully updated due to the measurements stopping in 2017 is a drawback.

The Basel Institute of Governance uses 17 variables from 5 distinct categories that are weighted and evaluated annually to generate the anti-money-laundering index (AML), the third economic and financial crime indicator, for 110 nations. On a scale from 0 to 10, where 0 represents the lowest susceptibility and 10 the worst vulnerability, it measures a nation's risk of money laundering and terrorism funding.

The World Bank database contains important statistics on the GDP per capita for all nations. It is calculated by dividing the official GDP, or the total gross value added by all the resident suppliers in a country's economy, by the total number of inhabitants, adding any applicable product taxes and deducting any discounts not factored into the price of the goods. It is calculated in US dollars.

The Environmental Performance Index (EPI) ranks 180 nations based on ecosystem health and environmental performance using 32 performance indicators divided into 11 pillars. Every two years, the Yale Centre for Environmental Law & Policy publishes it. The rating used spans from 0 (least eco-friendly) to 100 (most environmentally friendly).

CPI changed its measurement methodology in 2012, so, in order to have homogenous, consistent, and up-to-date data, the timeline of this study is from 2012 to 2021. However, the most recent data for NFCR is from 2020.

The descriptive statistics can be found in Table 3 below:

**Table 3.** Summary statistics

**Descriptive Statistics for All Countries**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| NFCR | 1590 | -.168 | 1.132 | -27.088 | 8.057 |
| CPI | 1754 | 43.065 | 19.411 | 8 | 92 |
| SE | 1068 | 25.649 | 11.527 | 4.8 | 58.2 |
| AML | 1418 | 5.669 | 1.218 | 2.34 | 8.61 |
| GDP | 1739 | 14.612 | 20.322 | .237 | 135.683 |
| EPI | 1660 | 55.068 | 16.009 | 15.47 | 90.68 |

**Descriptive Statistics for Developing Countries**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| NFCR | 1122 | -.291 | 1.262 | -27.088 | 8.057 |
| CPI | 1210 | 33.117 | 11.488 | 8 | 71 |
| SE | 626 | 32.637 | 8.685 | 11 | 58.2 |
| AML | 899 | 6.202 | 1.073 | 3.12 | 8.61 |
| GDP | 1188 | 4.037 | 3.48 | .237 | 34.758 |
| EPI | 1132 | 48.53 | 13.273 | 15.47 | 83.78 |

**Descriptive Statistics for Developed Countries**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| NFCR | 468 | .128 | .644 | -5.882 | 2.632 |
| CPI | 544 | 65.191 | 14.546 | 35 | 92 |
| SE | 442 | 15.752 | 6.862 | 4.8 | 40.2 |
| AML | 519 | 4.747 | .845 | 2.34 | 7.16 |
| GDP | 551 | 37.412 | 22.728 | 8.507 | 135.683 |
| EPI | 528 | 69.086 | 11.833 | 35.54 | 90.68 |

**Source:** own processing

The Net Forest Conversion Rate (NFCR) variable shows that Sudan shrank its forestland the most, by -27.0876% in 2012, as Burundi expended its forestland the most, in 2012, with 8.0569%.

Corruption Perception Index (CPI) presents Somalia, North Korea, and Afghanistan as the most corrupt countries in the world: the first two countries have a score of 8 out of 100 between the years 2012 to 2015, and the last in 2012 and 2013. At the opposite pole, Denmark registered the highest CPI score, meaning the lowest level of perceived corruption, in 2014: 92 out of 100.

The lowest value for shadow economy (SE) is recorded in the United States of America in 2019: underground economy of only 4.80% of GDP. Its highest level was measured in Bolivia in 2016, with an underground economy of 58.2% of GDP.

The Anti-money-laundering Index (AML) registered its minimum in Estonia in 2021: only 2.34 out of 10, meaning a very low vulnerability to terrorist financing and money-laundering activities. On the opposite pole, the maximum score is 8.61, and it is attributed to Iran, in 2016, resulting in Iran being the most vulnerable country to the risk of terrorist financing and money-laundering activities.

As for the GDP per capita, the lowest value is recorded in Burundi in 2021, only $236, oppositely to Luxemburg, in the same year, with $13568.

The Environmental Performance Index (EPI) registered the lowest score in 2014 in Somalia, of only 15.47 out of 100, ranking it the least eco-friendly country, as Finland in 2016 obtained the highest score, of 90.68, being the most eco-friendly country.

It can easily be observed that developed countries usually score the best, as the developing ones the lowest.

**4. Results & Discussion**

In order to test the hypothesis, the statistical software used is STATA. First step is to analyze the correlation matrix, as shown in Table 4. It can be observed that NFCR and CPI have a direct relation, which means that countries that shrank their forestland might be more corrupt (negative and low values of NFCR mean greater deforestation than afforestation, as low values of CPI mean higher levels of perceived corruption). The negative coefficient of SE anticipates that countries that shrank their forestland have higher level of shadow economy. The same goes for AML, pointing out that these countries also might have higher vulnerability to money laundering and terrorist financing. These preliminary findings are in line with the ones obtained by Cozma, Achim, & Safta (2022) and (Cozma, Cotoc, Vaidean, & Achim (2021).

The positive relationship between NFCR and GDP goes to the core purpose of the present paper, as it indicates that richer countries, developed ones, have higher NFCR values, meaning less shrinking or even growing forestland. The positive coefficient of EPI makes sense, as it shows that high levels of NFCR, meaning low net deforestation or even net afforestation, correspond to countries with high levels of EPI, eco-friendly countries.

**Table 4.** Correlation matrix

| | NFCR | CPI | SE | AML | GDP | EPI |
|---|---|---|---|---|---|---|
| NFCR | 1.0000 | | | | | |
| CPI | 0.3128 | 1.0000 | | | | |
| SE | -0.3257 | -0.7557 | 1.0000 | | | |
| AML | -0.3046 | -0.6843 | 0.5307 | 1.0000 | | |
| GDP | 0.2382 | 0.8332 | -0.7258 | -0.4926 | 1.0000 | |
| EPI | 0.2295 | 0.6427 | -0.5247 | -0.5844 | 0.5854 | 1.0000 |

**Source:** own processing

In order to avoid multicollinearity, as CPI, SE, AML, and GDP are related, a Variance Inflation Factor test was conducted. Its results show that only CPI has a value greater than 5 but only with 3 decimals. Because there are 2 different opinions in the statistical literature regarding the maximum value of VIF in order to avoid multicollinearity problems, one that considers 5 and one than considers 10, because the value of CPI is exceeding 5 with only 3 decimals, and because it is the most important economic and financial crime related to illegal deforestation, the CPI was not removed from the regressions.

**Table 5.** Variance Inflation Factor test

| | VIF | 1/VIF |
|---|---|---|
| CPI | 5.375 | .186 |
| GDP | 3.797 | .263 |
| SE | 2.467 | .405 |
| AML | 2.136 | .468 |
| EPI | 1.86 | .538 |
| Mean VIF | 3.127 | . |

**Source:** own processing

Firstly, regressions were conducted for all the countries, regardless of their developing status. In Table 6, it can be observed that the type of relations described for the correlation matrix are validated by these models. For the entire model, p-value is less than 0.05, which means the independent variables influence the dependent one. Because Pooled OLS neglects the specific characteristics of each individual country, and because the Hausman test shows a p-value greater than 0.05, the best is the Random-Effects model, which is normal, due to the fact that the data is changing in time. CPI and SE prove to be statistically significant, which means that there is a statistically significant relationship between deforestation and economic and financial crime. Similar results were obtained by Cozma, Achim, & Safta (2022) and (Cozma, Cotoc, Vaidean, & Achim (2021).

**Table 6.** Regressions of NFCR on CPI, SE, AML, GDP, and EPI, for all countires, regardless their developing status

**Pooled OLS Regression results**

| NFCR | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| CPI | .0057806 | .0033142 | 1.74 | .0815025 | -.0007248 | .0122859 | * |
| SE | -.0145739 | .0038676 | -3.77 | .0001763 | -.0221657 | -.0069822 | *** |
| AML | -.0923512 | .03336 | -2.77 | .0057629 | -.1578333 | -.0268692 | *** |
| GDP | -.0037716 | .0024718 | -1.53 | .1274293 | -.0086235 | .0010802 | |
| EPI | .0000864 | .0024755 | 0.03 | .9721553 | -.0047728 | .0049456 | |
| Constant | .5637311 | .3559892 | 1.58 | .1136827 | -.1350365 | 1.2624986 | |

| | | | |
|---|---|---|---|
| Mean dependent var | -0.1016749 | SD dependent var | 0.8767801 |
| R-squared | 0.1129640 | Number of obs | 818 |
| F-test | 20.6816405 | Prob > F | 0.0000000 |
| Akaike crit. (AIC) | 2019.1969792 | Bayesian crit. (BIC) | 2047.4381532 |

**** p<.01, ** p<.05, * p<.1*

**Random-Effects Regression results**

| NFCR | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| CPI | .0107176 | .0046947 | 2.28 | .022436 | .0015161 | .0199191 | ** |
| SE | -.0119549 | .0061384 | -1.95 | .0514686 | -.0239859 | .0000762 | * |
| AML | -.0449759 | .0401606 | -1.12 | .2627554 | -.1236892 | .0337374 | |
| GDP | -.0051193 | .0038516 | -1.33 | .1838102 | -.0126683 | .0024298 | |
| EPI | -.0031439 | .0015793 | -1.99 | .0465122 | -.0062392 | -.0000486 | ** |
| Constant | .19522 | .4170872 | 0.47 | .6397449 | -.6222559 | 1.0126959 | |

| | | | |
|---|---|---|---|
| Mean dependent var | -0.1016749 | SD dependent var | 0.8767801 |
| Overall r-squared | 0.1062621 | Number of obs | 818 |
| Chi-square | 24.2757300 | Prob > chi2 | 0.0001922 |
| R-squared within | 0.0076865 | R-squared between | 0.1381754 |

**** p<.01, ** p<.05, * p<.1*

**Fixed-Effects Regression results**

| NFCR | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| CPI | .0002475 | .0075305 | 0.03 | .9737923 | -.0145384 | .0150334 | |
| SE | -.0039913 | .0086923 | -0.46 | .6462526 | -.0210583 | .0130756 | |
| AML | -.0128682 | .0473369 | -0.27 | .7858254 | -.1058121 | .0800758 | |
| GDP | -.0120316 | .0057152 | -2.11 | .0356401 | -.0232531 | -.0008101 | ** |
| EPI | -.0043732 | .0016326 | -2.68 | .0075723 | -.0075788 | -.0011675 | *** |
| Constant | .5568687 | .5648799 | 0.99 | .3245732 | -.5522498 | 1.6659871 | |

| | | | |
|---|---|---|---|
| Mean dependent var | -0.1016749 | SD dependent var | 0.8767801 |
| R-squared | 0.0158102 | Number of obs | 818 |
| F-test | 2.1847247 | Prob > F | 0.0000000 |
| Akaike crit. (AIC) | 837.2379795 | Bayesian crit. (BIC) | 865.4791535 |

**** p<.01, ** p<.05, * p<.1*

**Hausman (1978) specification test**

| | Coef. |
|---|---|
| Chi-square test value | 10.43 |
| P-value | .064 |

**Source:** own processing

In Table 7, the results for the same statistical procedures were shown, but this time only for developing countries. The Random-Effects Regression model proves, once again, to be the best, as the p-value for the Hausman test is greater than 0.05, and, moreover, the Fixed-Effects Regression is not statistically significant (p-value greater than 0.05). The coeffcients for the economic and financial crime variables keep their signs. The R-squared for the developing countries is 10.043%, which means that 10.43% of NFCR variation is explained by the variation of the independent variables. An important aspect that needs to be adressed is that the GDP coefficient is positive, which means that richer developing countries have a lower deforestation rate. The same goes for EPI: more eco-friendly developing countries have a lower deforestation rate. It can also be observed that GDP and EPI are not significant

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for the deforestation rate in deveopling countries, but it is mostly linked to economic and financil crimes as shadow economy and money-laundering.

**Table 7.** Regressions of NFCR on CPI, SE, AML, GDP, and EPI, for developing countries

**Pooled OLS Regression results**

| NFCR | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| CPI | .0088506 | .0056627 | 1.56 | .1187631 | -.002278 | .0199792 | |
| SE | -.016708 | .0052211 | -3.20 | .0014712 | -.0269688 | -.0064472 | *** |
| AML | -.0241967 | .0508289 | -0.48 | .6342762 | -.1240889 | .0756955 | |
| GDP | .0602605 | .0151185 | 3.99 | .0000784 | .0305488 | .0899722 | *** |
| EPI | .0006138 | .003638 | 0.17 | .8660926 | -.0065359 | .0077635 | |
| Constant | -.2174699 | .544298 | -0.40 | .6896838 | -1.2871578 | .8522179 | |

| | | | |
|---|---|---|---|
| Mean dependent var | -0.3219064 | SD dependent var | 1.0016713 |
| R-squared | 0.1161958 | Number of obs | 455 |
| F-test | 11.8062140 | Prob > F | 0.0000000 |
| Akaike crit. (AIC) | 1247.5511381 | Bayesian crit. (BIC) | 1272.2729226 |

**** p<.01, ** p<.05, * p<.1*

**Random-Effects Regression results**

| NFCR | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| CPI | .0063639 | .007667 | 0.83 | .406521 | -.0086632 | .021391 | |
| SE | -.0136503 | .0076378 | -1.79 | .0739044 | -.0286202 | .0013195 | * |
| AML | -.0981401 | .0596014 | -1.65 | .0996386 | -.2149566 | .0186764 | * |
| GDP | .0269704 | .0216478 | 1.25 | .2128119 | -.0154586 | .0693994 | |
| EPI | .0020521 | .0018555 | 1.11 | .2687527 | -.0015847 | .0056889 | |
| Constant | .2990949 | .6192946 | 0.48 | .6291237 | -.9147003 | 1.51289 | |

| | | | |
|---|---|---|---|
| Mean dependent var | -0.3219064 | SD dependent var | 1.0016713 |
| Overall r-squared | 0.1043419 | Number of obs | 455 |
| Chi-square | 13.9568657 | Prob > chi2 | 0.0158857 |
| R-squared within | 0.0086564 | R-squared between | 0.1268006 |

**** p<.01, ** p<.05, * p<.1*

**Fixed-Effects Regression results**

| NFCR | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| CPI | .0029009 | .0103865 | 0.28 | .7801739 | -.0175241 | .023326 | |
| SE | -.0104226 | .010285 | -1.01 | .3115494 | -.0306481 | .0098028 | |
| AML | -.1175254 | .0716781 | -1.64 | .1019467 | -.2584806 | .0234298 | |
| GDP | -.0003572 | .0318604 | -0.01 | .9910617 | -.0630107 | .0622964 | |
| EPI | .0015773 | .0019395 | 0.81 | .4166072 | -.0022368 | .0053914 | |
| Constant | .5837438 | .7384017 | 0.79 | .4297211 | -.868325 | 2.0358127 | |

| | | | |
|---|---|---|---|
| Mean dependent var | -0.3219064 | SD dependent var | 1.0016713 |
| R-squared | 0.0109583 | Number of obs | 455 |
| F-test | 0.8066052 | Prob > F | 0.8902114 |
| Akaike crit. (AIC) | 382.6657261 | Bayesian crit. (BIC) | 407.3875106 |

**** p<.01, ** p<.05, * p<.1*

**Hausman (1978) specification test**

| | Coef. |
|---|---|
| Chi-square test value | 3.549 |
| P-value | .616 |

**Source:** own processing

In Table 8, the results for developed countries are shown. The Hausman test shows again that the Random-Effects Regression model is, again, the best. The coeffcients for the economic and financial crime variables keep their signs, exept SE, and CPI proves to be statistically significant. The R-squared for the developed countries is 5.63%, which means that only 5.63% of NFCR variation is explained by the variation of the independent variables. This is half of the value obtained for the developing countries. The positive sign of SE should not be of concern, as it is not a significant variable in the model. However, it must be noticed that EPI proves to be significant, which means that the environmental performance of a developed country plays an important role in its deforestation rate, as does corruption. This time, the GDP coefficient is negative, meaning that richer developed countries have a higher deforestation rate.

**Table 8.** Regressions of NFCR on CPI, SE, AML, GDP, and EPI, for developed countries

**Pooled OLS Regression results**

| NFCR | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| CPI | .0087223 | .0033068 | 2.64 | .0087125 | .002219 | .0152256 | *** |
| SE | .0169079 | .0062728 | 2.70 | .0073624 | .0045716 | .0292442 | *** |
| AML | -.0412053 | .041696 | -0.99 | .323709 | -.123206 | .0407954 | |
| GDP | -.0003332 | .0021997 | -0.15 | .8796797 | -.0046593 | .0039929 | |
| EPI | -.0094546 | .003023 | -3.13 | .0019074 | -.0153997 | -.0035095 | *** |
| Constant | .2158072 | .4054158 | 0.53 | .5948419 | -.5814962 | 1.0131106 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 0.1743728 | SD dependent var | 0.5824664 |
| R-squared | 0.0646194 | Number of obs | 363 |

| | | | |
|---|---|---|---|
| F-test | 4.9325658 | Prob > F | 0.0002222 |
| Akaike crit. (AIC) | 624.5077538 | Bayesian crit. (BIC) | 647.8741708 |

**** p<.01, ** p<.05, * p<.1*

**Random-Effects Regression results**

| NFCR | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| CPI | .0117163 | .0051173 | 2.29 | .0220471 | .0016866 | .021746 | ** |
| SE | .0103952 | .0097909 | 1.06 | .2883636 | -.0087947 | .0295851 | |
| AML | -.0020086 | .0527862 | -0.04 | .9696464 | -.1054676 | .1014504 | |
| GDP | -.0042617 | .0034425 | -1.24 | .2157241 | -.0110089 | .0024854 | |
| EPI | -.0119259 | .0027235 | -4.38 | .0000119 | -.017264 | -.0065879 | *** |
| Constant | .2502756 | .509821 | 0.49 | .623491 | -.7489552 | 1.2495064 | |

| | | | |
|---|---|---|---|
| Mean dependent var | 0.1743728 | SD dependent var | 0.5824664 |
| Overall r-squared | 0.0563682 | Number of obs | 363 |
| Chi-square | 24.3261878 | Prob > chi2 | 0.0001879 |
| R-squared within | 0.0658454 | R-squared between | 0.0501287 |

**** p<.01, ** p<.05, * p<.1*

**Fixed-Effects Regression results**

| NFCR | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| CPI | -.0032218 | .0108885 | -0.30 | .7675083 | -.0246462 | .0182026 | |
| SE | -.004059 | .0166924 | -0.24 | .8080366 | -.0369033 | .0287852 | |
| AML | .0306611 | .0653796 | 0.47 | .6394199 | -.0979813 | .1593034 | |
| GDP | -.0149147 | .0062214 | -2.40 | .0171053 | -.027156 | -.0026733 | ** |
| EPI | -.0139739 | .0028449 | -4.91 | 1.500e-06 | -.0195716 | -.0083762 | *** |
| Constant | 1.8879732 | .9850834 | 1.92 | .0562099 | -.0502978 | 3.8262442 | * |

| | | | |
|---|---|---|---|
| Mean dependent var | 0.1743728 | SD dependent var | 0.5824664 |
| R-squared | 0.0812628 | Number of obs | 363 |
| F-test | 5.5016198 | Prob > F | 0.0000000 |
| Akaike crit. (AIC) | 427.2843271 | Bayesian crit. (BIC) | 450.6507441 |

**** p<.01, ** p<.05, * p<.1*

**Hausman (1978) specification test**

| | Coef. |
|---|---|
| Chi-square test value | 9.964 |
| P-value | .076 |

**Source:** own processing

Regarding the different GDP coefficient signs, positive for developing countries and negative for developed countries, similar results as the ones obtained in this study for developing countries were also obtained by Mendes and Porto Junior (2012), who demonstrated that the economic growth is statistically significant in a direct relationship to the degree of illicit deforestation by focusing primarily on Brazilian towns in the Amazon area.

Furthermore, according to Ewers (2006), "there is a strong interaction between forest cover and economic development that determines rates of forest change among nations". According to Laurance's research, low-income nations see the greatest loss of forests and are "plagued by endemic corruption" (2007). However, according to Bakehe (2020), the maintenance of forest cover is negatively correlated with GDP per capita, just as the present study shows it applied for developed countries.

Taking all of these into consideration, once again, it is confirmed that economic and financial crimes have a significant influence on deforestation, in general, as countries that present higher levels of deforestation are also countries with high levels of corruption, shadow economy, and vulnerability to money-laundering. The results prove to be mostly robust, and the hypothesis that economic and financial crime has a higer impact on the rate of deforestation in developing countries is confirmed, as R-squared for developing countries is 10.43%, as for developed countries at half: only 5.63%.

## 5. Conclusions

In order to have a wide perspective on the deforestation phenomenon, looking only at numbers is insufficient. Only when one considers both the numbers and actual real-life circumstances does it become sufficient. Determinants of deforestation must be recognized both qualitatively and quantitatively in order to achieve this. The theory developed through interviews, focus groups, other publications, and case studies is crucial, but it must be backed up with quantitative investigations that are fact-based.

The importance of the present research is to offer a quantitative proof that economic and financial crime influences the deforestation rate, but with different intensities depending on the development phase of a country. It shows that the focus of stakeholders should be mostly on developing countries when trying to reduce the deforestation rate by lowering the levels of economic and financial crimes rate. That is because the regressions applied to the database show that both developed and developing countries present a direct connection between economic and financial crime and the level of deforestation, but in developed countries the influence of economic and financial crime on deforestation is lower.

Better understanding of this phenomenon and the differences that appear between different types of countries can contribute to the identification of more effective solutions and more efficient implementation of these remedies.

The study has some limitations, which lead to a relatively low number of observations when more variables are taken into account, including the availability of data, changes in the methodology for measuring the indicators, the slow updating of the databases, and the different approaches to creating datasets. Research in the future may concentrate on enhancing the models by including more significant variables and increasing the R-squared in order to account for a greater proportion of the variability of the dependent variable.

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**Appendix**

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|---|---|---|
| 1. Afghanistan - Developing | 2. Albania - Developing | 3. Algeria - Developing |
| 4. Angola - Developing | 5. Argentina - Developing | 6. Armenia - Developing |
| 7. Australia - Developed | 8. Austria - Developed | 9. Azerbaijan - Developing |
| 10. Bahamas - Developed | 11. Bahrain - Developed | 12. Bangladesh - Developing |
| 13. Barbados - Developed | 14. Belarus - Developing | 15. Belgium - Developed |
| 16. Belize - Developing | 17. Benin - Developing | 18. Bhutan - Developing |
| 19. Bolivia - Developing | 20. Bosnia and Herzegovina - Developing | 21. Botswana - Developing |
| 22. Brazil - Developing | 23. Brunei Darussalam - Developed | 24. Bulgaria - Developing |
| 25. Burkina Faso - Developing | 26. Burundi - Developing | 27. Cambodia - Developing |
| 28. Cameroon - Developing | 29. Canada - Developed | 30. Cape Verde - Developing |
| 31. Central African Republic - Developing | 32. Chad - Developing | 33. Chile - Developed |
| 34. China - Developing | 35. Colombia - Developing | 36. Comoros - Developing |
| 37. Congo Democratic Republic - Developing | 38. Congo Republic - Developing | 39. Costa Rica - Developing |
| 40. Côte d´Ivoire - Developing | 41. Croatia - Developed | 42. Cuba - Developing |
| 43. Cyprus - Developed | 44. Czech Republic - Developed | 45. Denmark - Developed |
| 46. Djibouti - Developing | 47. Dominica - Developing | 48. Dominican Republic - Developing |
| 49. Ecuador - Developing | 50. Egypt - Developing | 51. El Salvador - Developing |
| 52. Equatorial Guinea - Developing | 53. Eritrea - Developing | 54. Estonia - Developed |
| 55. Ethiopia - Developing | 56. Finland - Developed | 57. France - Developed |
| 58. Gabon - Developing | 59. Gambia - Developing | 60. Georgia - Developing |
| 61. Germany - Developed | 62. Ghana - Developing | 63. Greece - Developed |
| 64. Grenada - Developing | 65. Guatemala - Developing | 66. Guinea - Developing |
| 67. Guinea-Bissau - Developing | 68. Guyana - Developing | 69. Haiti - Developing |
| 70. Honduras - Developing | 71. Hong Kong - Developed | 72. Hungary - Developed |
| 73. Iceland - Developed | 74. India - Developing | 75. Indonesia - Developing |
| 76. Iran - Developing | 77. Iraq - Developing | 78. Ireland - Developed |
| 79. Israel - Developed | 80. Italy - Developed | 81. Jamaica - Developing |
| 82. Japan - Developed | 83. Jordan - Developing | 84. Kazakhstan - Developing |
| 85. Kenya - Developing | 86. Kiribati - Developing | 87. Korea (North) - Developing |
| 88. Kosovo - Developing | 89. Kuwait - Developed | 90. Kyrgyzstan - Developing |
| 91. Laos - Developing | 92. Latvia - Developed | 93. Lebanon - Developing |

| | | |
|---|---|---|
| 94. Lesotho - Developing | 95. Liberia - Developing | 96. Libya - Developing |
| 97. Lithuania - Developed | 98. Luxembourg - Developed | 99. Macao - Developed |
| 100. Macedonia - Developing | 101. Madagascar - Developing | 102. Malawi - Developing |
| 103. Malaysia - Developing | 104. Maldives - Developing | 105. Mali - Developing |
| 106. Malta - Developed | 107. Mauritania - Developing | 108. Mauritius - Developed |
| 109. Mexico - Developing | 110. Moldova - Developing | 111. Mongolia - Developing |
| 112. Montenegro - Developing | 113. Morocco - Developing | 114. Mozambique - Developing |
| 115. Myanmar - Developing | 116. Namibia - Developing | 117. Nepal - Developing |
| 118. Netherlands - Developed | 119. New Zealand - Developed | 120. Nicaragua - Developing |
| 121. Niger - Developing | 122. Nigeria - Developing | 123. Norway - Developed |
| 124. Oman - Developed | 125. Pakistan - Developing | 126. Panama - Developed |
| 127. Papua New Guinea - Developing | 128. Paraguay - Developing | 129. Peru - Developing |
| 130. Philippines - Developing | 131. Poland - Developed | 132. Portugal - Developed |
| 133. Puerto Rico - Developed | 134. Qatar - Developed | 135. Romania - Developed |
| 136. Russia - Developing | 137. Rwanda - Developing | 138. Saint Lucia - Developing |
| 139. Saint Vincent and the Grenadines - Developing | 140. Samoa - Developing | 141. Sao Tome and Principe - Developing |
| 142. Saudi Arabia - Developed | 143. Senegal - Developing | 144. Serbia - Developing |
| 145. Seychelles - Developed | 146. Sierra Leone - Developing | 147. Singapore - Developed |
| 148. Slovakia - Developed | 149. Slovenia - Developed | 150. Somalia - Developing |
| 151. South Africa - Developing | 152. South Korea - Developed | 153. South Sudan - Developing |
| 154. Spain - Developed | 155. Sri Lanka - Developing | 156. Sudan - Developing |
| 157. Suriname - Developing | 158. Swaziland - Developing | 159. Sweden - Developed |
| 160. Switzerland - Developed | 161. Syria - Developing | 162. Taiwan - Developed |
| 163. Tajikistan - Developing | 164. Tanzania - Developing | 165. Thailand - Developing |
| 166. Timor-Leste - Developing | 167. Togo - Developing | 168. Tonga - Developing |
| 169. Trinidad and Tobago - Developed | 170. Tunisia - Developing | 171. Turkey - Developing |
| 172. Turkmenistan - Developing | 173. Uganda - Developing | 174. Ukraine - Developing |
| 175. United Arab Emirates - Developed | 176. United Kingdom - Developed | 177. United States of America - Developed |
| 178. Uruguay - Developed | 179. Uzbekistan - Developing | 180. Vanuatu - Developing |
| 181. Venezuela - Developing | 182. Viet Nam - Developing | 183. Yemen - Developing |
| 184. Zambia - Developing | 185. Zimbabwe - Developing | |