The Effect of Unemployment on the Decision to Enter the Illegal Ivory Trade

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ABSTRACT

Poaching threatens a wide array of species, including marine animals like molluscs and sharks, large wild cats such as leopards and tigers, and, perhaps most infamously, pachyderms such as rhinoceroses and elephants. Elephants are regarded as one of the "Big Five" species that attract significant numbers of tourists to many African countries. Most of the countries within African elephants' range are developing nations, so the demise of this species could have long-term negative effects on local economies. Economists commonly propose either the reinstatement of a legal ivory trade or an increase in the detection of or punishments for poachers as strategies to save the African elephant. However, few studies argue for economic development as a conservation strategy. The specific research question I investigate is: How do changes in the unemployment rate affect the number of illegally killed elephants within a district? I use the Monitoring the Illegal Killing of Elephants (MIKE) dataset the Convention on International Trade in Endangered Species (CITES) publishes as well as demographic data from the Integrated Public Use Microdata Series International (IPUMS-International) to answer this question, using a district-level fixed effects regression. I find that a one percentage point increase in the unemployment rate of an African district leads to approximately 3 to 4.6 more poached elephants in a given year. This evidence that unemployment affects the decision to enter the illegal ivory trade supports the notion that economic development is necessary to ensure the long-term survival of the African elephant.

I. Introduction

Globally, the illicit wildlife trade generates an estimated $7-23 billion per year (Nellemann, Henriksen, Raxter, Ash, & Mrema, 2014). A black market this large has serious repercussions for both the economies and the ecosystems of countries where wildlife trafficking takes place. This industry effectively robs the nations whose natural resources are unsustainably exploited (most of which are developing nations), while benefiting a relatively small population of those involved in the trade (Nellemann et al., 2014). Poaching threatens a variety of species, including marine animals like molluscs and sharks, large wild cats such as leopards and tigers, and, perhaps most infamously, pachyderms such as rhinoceroses and elephants.

There was once a legal international ivory trade, where the horns and tusks of rhinoceroses and elephants, respectively, could be harvested and traded internationally. However, the Convention on International Trade in Endangered Species (CITES) banned the international trade in African elephant ivory in 1989 to combat dwindling elephant populations (Stiles & Martin, 2001). The theory was that the legal ivory trade stimulated demand for ivory, and illegally obtained ivory was nearly impossible to detect and was thus laundered into the trade, contributing to high poaching rates prior to 1989 (Stiles & Martin, 2001). The ban was initially successful in decreasing the rate of elephant poaching, but there was a resurgence in the early 2000's which continues to this day (Stiles & Martin, 2001).

Over the course of the past century, the African elephant population has been shrinking at an alarming rate. The World Wildlife Fund estimates that there were an upper-bound of ten million African elephants less than a century ago, compared to only 415,000 today (2018). Recent estimates for the number of African elephants poached each year range from 22,000-25,000 (Nellemann et al., 2014). The African forest elephant population in particular decreased by approximately 62% in the period from 2002-2011 (Nellemann et al., 2014). While the rate of poaching has marginally declined each year since its peak in 2011 alongside a gradually increasing rate of illegal ivory seizures, the progress has not been sufficient for the survival of the African elephant in the long term (CITES, 2017).

Various phenomena contribute to the global decline in African elephants, including habitat loss, drought, climate change, and, of course, poaching (CITES, 2014). African elephant poaching comes in varying forms as well; examples include the illegal killing of elephants as a result of human-elephant conflict, for bushmeat during economic downturns, and for selling their ivory tusks in the black market (Barbier, Burgess, Swanson, & Pearce, 1990). However, poaching for the sake of ivory has been shown to be the most powerful contributor to declining African elephant populations globally (Wittemyer et al., 2014).

The survival of African elephants is imperative for the economic and environmental health of the regions they roam. Elephants play an important role in maintaining balance within ecosystems, and they are also regarded as one of the “Big Five” species which attract significant numbers of tourists to many African countries (Barbier, Burgess, Swanson, & Pearce, 1990). Furthermore, most of the countries within African elephants’ range are developing nations, so the demise of this species could have long-term negative effects on their local economies. The research question I investigate is: How do changes in the unemployment rate affect the number of African elephants poached within a district in a given year?

II. Literature Review

Economists most commonly propose either the reinstatement of a legal ivory trade (van Kooten, 2008) or increasing detection of or punishments for poachers (Leader-Williams & Milner-Gulland, 1993) to decrease the rate of African elephant poaching. In the case of the latter two proposals, Gary Becker’s (1968) seminal economic model of crime can explain poachers’ behavior. Under this model, the decision to commit a crime involves maximizing one’s expected utility from the offense. The motivations behind poaching do not differ significantly from the economic incentives behind crimes such as theft or drug smuggling. Applying Becker’s model, poachers are assumed risk neutral, and their utility increases with additional income (Abbott, 2008). Then, agents seek to optimize their utility through either legitimate employment or poaching, where they consider the potential wages they can earn in legitimate employment against the price for which they could sell poached ivory subject to the risk of detection and the cost of punishment (Abbott, 2008). Therefore, this theory suggests poverty, unemployment, and insufficient alternative labor market opportunities factor into an agent’s decision to poach.

One avenue Becker's model implies can be used to reach the optimal solution to the African elephant poaching crisis is for law enforcement to maximize the convictions and sentences of poachers subject to the cost of detection. In the case of Luangwa Valley, Zambia, increasing the rate of detection of poachers more effectively spared pachyderm populations than increasing the severity of sentences for those caught poaching (Leader-Williams & Milner-Gulland, 1993). Increasing sentences for those poaching offenders generate revenue, however, whereas detection efforts can be costly. Promising bioforensic innovations within the past five nears now allow researchers to track the source location of seized ivory, leading to more targeted prevention and detection measures that may correspond to more cost-effective detection (Wasser et al., 2015).

The economics of crime model also treats legitimate employment opportunities and the income they yield as substitutes for income-generating criminal offenses like poaching. Anecdotal evidence from enforcement rangers for Queen Elizabeth National Park in Uganda reveals mixed opinions on the exact role unemployment and poverty play in leading people to poach (Moreto & Lemieux, 2015). While one ranger believed elephant poachers were "unemployed [and were] fighting for livelihood," another contested that while poachers are unsatisfied with the jobs available to them, they do not necessarily lack alternative options altogether. He insisted potential poachers had opportunities in his community to do agricultural jobs or brick-laying, but they craved the white-collar status poaching allows, when these agents would typically not meet the qualifications for those jobs. The fairly quick profits one can earn poaching are what some rangers believe entice poachers. These accounts exemplify the uncertainty that permeates around whether unemployment alone persuades people to poach or if unsatisfactory employment opportunities are to blame.

Economists do not typically propose economic development as a conservation strategy, although this may be crucial to successfully deter wildlife trafficking in the long run. Political economic critiques of the discourse surrounding poaching have pointed out that conservation strategies often center around narrowing opportunities for impoverished individuals to earn a living (Lynch, Stretesky, & Long, 2017). While different theories exist about what the relationship between poverty alleviation and biodiversity conservation should be, one position considers how poverty can act as a “critical constraint” on conservation capabilities (Duffy, John, Büscher, & Brockington, 2015). Under this viewpoint, endangered species conservation is a normal good that citizens would be willing to pay for if their incomes could support it. When extensive wildlife poaching occurs in a developing nation then, as is the case for African elephant poaching, fruitful conservation strategies must coincide with economic development.

Although not the most prevalent in the literature, previous studies have drawn links between socioeconomic conditions and poaching. One such study used a generalized linear mixed-effects model to analyze how socioeconomic variables impact the rate of poaching of the saiga antelope in the Soviet Union, which found that unemployment had a positive effect on the poaching of the endangered species. Meanwhile, attitudes towards the species were irrelevant (Kühl et al., 2009). This offers credence to the position that poaching is economically motivated, not the result of animosity towards species.

I believe two previous studies have researched the impact of socioeconomic variables on African elephant poaching, and both accomplished this within a Kenyan context. The first study found that economic downturns, as indicated by local cattle and maize prices, led to higher rates of elephant poaching (Wittemyer, 2011). Kenya’s macroeconomic conditions were not significant predictors of poaching in this paper, which the author attributes to the dominance of subsistence farming in the region. This suggests further studies should focus on local economic indicators. Furthermore, this paper discusses how the age of an illegally killed elephant can help researchers determine whether the elephant was poached for the ivory trade, which targets mature elephants, or for bushmeat consumption during times of desperation, as elephant bushmeat is considered an inferior good. The second study of elephant poaching in a Kenyan region found that poverty is a significant predictor (Ouko, 2013). These studies offer evidence about the role local economic conditions play in African elephant poaching within Kenya, but these results have not been shown to generalize for the diverse contexts of other sub-Saharan African nations within elephants’ range. I contribute to the literature by being the first to analyze the effect of local economic conditions, particularly changes in unemployment rates, on the rate of elephant poaching for districts across the African continent.

III. Data

In my analysis, I use the Monitoring the Illegal Killing of Elephants (MIKE) dataset which the Convention on International Trade in Endangered Species (CITES) publishes. MIKE is a panel dataset which includes the total number of elephant carcasses found at each monitoring site within thirty African countries for the years 2002-2018. This total includes both carcassses of elephants which patrols deemed to have died of natural causes (such as old age, sickness, or drought) as well as the number of carcasses considered the result of poaching (referred to as illegal carcasses in the data). The sample of African elephants at MIKE sites represents an estimated 30-40% of the total continental elephant population (Mill, 2017).

The MIKE dataset includes 657 observations across all sites and years. The data are representative of each of the four African regions, as **Table 1** shows. The dataset includes over one hundred observations for each of the regions.

Table 1: *Discovered Elephant Carcasses by Region (Entire Sample)*

Region	Number of Districts	Number of Observations	Total Number of Carcasses	Number of Illegal Carcasses	Percentage of Carcasses Killed Illegally
Central Africa	11	176	3,545	2,766	78.0%
Eastern Africa	15	192	8,675	3,860	44.5%
Southern Africa	13	156	6,469	2,353	36.4%
West Africa	14	133	814	579	71.1%
Grand Total	**53**	**657**	**19,503**	**9,558**	**49.0%**

As shown in **Table 1**, the largest volume of elephants is poached in the Eastern region of Africa, while the highest percentage of carcassses that were killed illegally occurs in Central Africa. Overall, approximately half of the elephant carcasses recorded in MIKE are from poaching. A limitation of the MIKE dataset is it only provides information on the number of detected elephant carcasses, not on the number of living elephants in the same region. Higher total numbers of carcasses in a region likely coincide with greater concentrations of elephants residing there, but the exact relationship is not clear from these data.

I merge the MIKE dataset with socioeconomic data from Integrated Public Use Microdata Series International (IPUMS-International) by district and year. The availability of data through IPUMS-International differs substantially by country. From this dataset, in which each observation represents one individual, I use the variables for district of residence, employment status, level of educational attainment, and industry because these were the most universally available. Using these, I create district-level demographic variables for the unemployment rate, the population, the percentage of the district with less than a primary education, and the percentage employed in the agriculture industry.

Table 2 describes the district-level averages of the demographic variables for each of the four regions of Africa using the analytic sample. Unemployment is most prevalent in Central Africa, at an average rate of 15.5%, which is almost seven times West Africa's average of 2.26%. The average district in the analytic sample has approximately 278,540 residents. Educational attainment is highest in Central Africa, with 56.48% of the population at less than a primary level of education, compared to West Africa's 82.95%. The majority of employees in all regions work within the agricultural industry, at an average of 69.4% overall.

Table 2: *Averages of District-Level Demographic Variables by Region (Analytic Sample)*

Region	Unemployment Rate	Population	% With Less than Primary Education	% of District in Agriculture	Frequency
Central Africa	15.50 (4.70)	126,666 (68,263.38)	56.48 (6.18)	74.32 (3.98)	2
Eastern Africa	2.65 (0.88)	254,950.18 (147,685.63)	60.47 (9.37)	77.27 (8.92)	11
Southern Africa	13.38 (16.82)	420,004 (519,800.54)	65.36 (23.28)	60.66 (35.78)	10
West Africa	2.26 (1.61)	156,911.14 (69,722.77)	82.95 (13.34)	68.11 (11.81)	7

Total	6.99 (11.00)	278,540.1 (323,749.55)	67.08 (17.96)	69.40 (22.50)	30
Note: Standard deviations in parentheses.					

Demographic data from IPUMS-International is sparse across Africa compared to other continents in the dataset. Those who compile and disseminate IPUMS-International data attribute this discrepancy to a lack of cooperation from African countries' National Statistics Offices (McCaa, R., & Thomas, W., 2009). Thus, my analytic sample drops to only 30 observations, in contrast to the 657 observations in the entire sample. For more information on the analytic sample, **Table A.1** in the Appendix shows the geographic breakdown of the analytic sample in terms of region, country, and district. In addition, the **Figures A.1-A.4** show comparisons between the analytic sample and the entire sample.

Table 3 shows a balance table which compares the mean values of the variables used in my analysis across the entire sample versus those with only partial demographic data from the IPUMS-International dataset versus those that make it into the final analytic sample. The only statistically significant difference is between the average population of districts in the analytic sample and the sample with partial demographic data, in part due to the wide standard errors. To account for this difference, I introduce variables IllegHT and TotHT to represent the number of illegal elephant carcasses and the total number of elephant carcasses found per one hundred thousand people, respectively.

Table 3: *Balance Table Comparing District Averages for the Entire Sample, Observations with Partial Demographic Data, and the Analytic Sample*

		District Averages		
Source Dataset	**Variables**	**Entire Sample**	**Partial Demographic Data**	**Analytic Sample**
Elephant Carcass Data (MIKE)	Total Number of Carcasses	29.24 (51.89)	32.29 (73.97)	17.90 (33.87)
	Number of Illegal Carcasses	14.33 (26.70)	12.44 (21.95)	10.00 (19.46)
Demographic Data (IPUMS-International)	Unemployment Rate	-	7.68 (10.77)	6.99 (11.00)
	Population	-	405,837.34 (569,795.79)	278,540.10*** (323,749.60)
	% with Less than Primary Education	-	66.66 (18.51)	67.08 (17.96)
	% in Agriculture	-	-	69.40 (22.50)
	Observations	667	41	30

Note: ** p < 0.1, ** p < 0.05, *** p < 0.01.* Standard errors in parentheses.

IV. Methodology

In an ideal world, I would have individual-level data and be able to see a person's employment status, level of education, income, available alternative employment opportunities, and most importantly, whether they have ever poached and, if so, how many elephants they poached within a given time period. These types of regressions would lend clear evidence about the roles unemployment and other socioeconomic factors play in the poaching decision. However, this is highly impractical. By the very nature of illegal wildlife poaching, most of the poachers go undetected and are unavailable for observation. Additionally, individual measures of socioeconomic factors do not exist to the extent I would need to complete this analysis.

Rather, I use a district-level, fixed effect regression in order to control for unobserved, time-invariant variables for each district included in my data. Included amongst these variables is the relative concentration of elephants in each particular region. Note, this relies on the assumption that elephants' ranges across the African continent have been constant over time, an assumption that may be incorrect given shifting ranges due to habitat loss and shifting availability of water from climate change. My analysis also relies on the assumption that the idiosyncratic error terms are homoskedastic and serially uncorrelated. I have an unbalanced panel of data, with many districts lacking data for certain periods, which I treat as a pooled cross-section in my analysis.

The fixed effects model I estimate using pooled OLS is

$$IllegCarc_{it} = \alpha + \beta_1 Unemp_{it} + \beta_2 PercAg_{it} + \beta_3 PercLessPrim_{it} + \beta_4 Log(Pop)_{it} + \beta_5 TotCarc_{it} + \gamma_i + \varepsilon_{it}$$

where the *i* subscripts represent each district, the *t* subscripts represent each year, $Illegcarc_{it}$ is the number of discovered carcasses that were killed illegally, and $TotCarc_{it}$ is the total number of carcasses found for each district. The variable $Unemp_{it}$ represents the district's unemployment rate, $PercAg_{it}$ is the percent of the working population of the district in the agriculture industry, $PercLessPrim_{it}$ is the percent of the district with less than a primary education, $Log(Pop)_{it}$ is the logged population of the district, γ_i is the district-specific fixed effect, and ε_{it} is the idiosyncratic error term.

As a robustness measure, I also estimate a similar district fixed effects model using the variable I introduced, the number of illegally killed elephants per one hundred thousand people, as the dependent variable. As stated previously, this attempts to correct for the statistically significant difference between the populations of districts with partial demographic data and those that make it into the analytic sample. The regression I run for this is:

$$IllegHT_{it} = \alpha + \beta_1 Unemp_{it} + \beta_2 PercAg_{it} + \beta_3 PercLessPrim_{it} + \beta_5 TotHT_{it} + \gamma_i + \varepsilon_{it}$$

where $IllegHT_{it}$ represents the number of illegal carrcasses found per one hundred thousand people in a district, and $TotHT_{it}$ represents the total number of carcasses found per one hundred thousand people.

Lastly, I estimate a model using the proportion of elephant carcasses that were killed illegally ($PropIllegal_{it}$) as my dependent variable. This is not my preferred model because it homogenizes the variation between districts significantly. For example, a district with zero poached carcasses and one thousand total carcasses is calculated to have the same proportion killed illegally as a district with zero illegally killed carcasses and one carcass total per year. Clearly, the district with one thousand total carcasses and zero poached carcasses is doing a much better job at conservation. A similar argument can be made for districts with one hundred percent of discovered carcasses being caused by poaching in a given year. Nonetheless, the equation for this model is:

$$PropIllegal_{it} = \alpha + \beta_1 Unemp_{it} + \beta_2 PercAg_{it} + \beta_3 PercLessPrim_{it} + \beta_4 Log(Pop)_{it} + \gamma_i + \varepsilon_{it}$$

I also estimate each of these equations without district-level fixed effects. Considering the limited number of variables my dataset includes and the small size of my dataset, fixed effects is my preferred model to best account for unobserved differences between districts. However, the fixed effects models require more than one year of data for each district, so only the eight shaded districts in **Table A.1** contribute to the results of these models, a considerable limitation of my analysis.

V. Results

Table 4 states the results for three district fixed effects models and one OLS regression using the number of elephant carcasses killed illegally as the dependent variable. In model (1), after controlling for district-level fixed effects and other variables, a one percentage point increase in the unemployment rate corresponds to approximately three more illegally killed elephant carcasses discovered in a given year, and this result is statistically significant at the 1% level. The magnitude of the result increases when I added a control variable for the population size of the district in regression (2), to approximately 4.6 more elephants poached each year for every additional one percentage point of unemployment in a district, at a 5% significance level. In regression (3), the coefficient on the unemployment rate remains high but is no longer significant. The fact that I was able to see significant results with such a small sample size, especially with nontrivial magnitudes on the coefficients, suggests a positive relationship between changes in unemployment within an African district and the prevalence of poaching within the district.

Table 4: Results in Terms of Number of Elephant Carcasses Killed Illegally

	Regression			
Independent Variables	**(1)**	**(2)**	**(3)**	**(4)**
Unemployment Rate	2.963*** (0.473)	4.572** (1.586)	4.587* (1.891)	-0.283* (0.151)
Total Number of Carcasses	0.531*** (0.022)	0.542*** (0.025)	0.542*** (0.033)	0.549*** (0.029)
% in Agriculture	-0.665*** (0.131)	-0.786*** (0.172)	-0.788** (0.209)	-0.032 (0.067)
Log(Population)	-	-7.409 (6.978)	-7.481 (8.377)	1.005 (1.624)
% with Less than Primary Education	-	-	-0.008 (0.260)	0.002 (0.071)
District FE	**Y**	**Y**	**Y**	**N**
R-Squared	0.9977	0.9982	0.9982	0.9495
Adjusted R-Squared	0.9866	0.9869	0.9825	0.9390
Observations	30	30	30	30
Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors in parentheses.				

Unsurprisingly, the total number of carcasses discovered at a district site in a given year is an extremely significant indicator of the number of illegally killed elephant carcasses for the same year. This variable aims to control for areas that host a larger elephant population. In line with the summary statistics, this variable suggests that for every two elephant carcasses discovered, approximately one of them will have been poached, and the other will have died from natural causes.

The percentage of the district's employed involved in agriculture is significant in each of my regressions. The regressions suggest a one percentage point increase in the percent of the district that partakes in agricultural work leads to between 0.65 to 0.79 fewer illegal elephant carcasses found in a given year. This result is counter to my intuition on illegal elephant killings. I would have assumed that, holding unemployment constant, more prevalence of agriculture in a region would lead to more illegal elephant killings. There is evidence that human-elephant conflict can arise around crop destruction (Barbier, Burgess, Swanson, & Pearce, 1990), so I would have assumed a positive coefficient on this variable. However, this coefficient could also be negative due to omitted variable bias for variables I cannot observe in my data. One explanation for this result may be that a decreased amount of the population of a district being employed in agriculture over time could correspond to droughts affecting within-district food markets. Then, this coefficient may be picking up on that some of the poaching that comes from the demand for elephant bushmeat in times of local economic downturns from droughts.

Neither my control variable for district population size nor educational attainment are significant in any of my regressions. Nonetheless, the inclusion of these variables seems to have cut back on some of the noise in the other independent variables, allowing the coefficients on them to increase. For the variable of interest, unemployment, the increased magnitude of the coefficient comes at the cost of statistical significance with the addition of each control variable.

Regression (4), the regression without district-level fixed effects, is not my preferred model. Nonetheless, this model highlights that the results I see in the first three regressions are specific to within-district changes in unemployment rates and other factors,which does not necessarily apply across districts. Across districts, I find a negative coefficient on unemployment, -0.283, statistically significant at the 10% level. This suggests there are confounding variables surrounding unemployment that inflict omitted variable bias when comparing across districts.

The R^2 and adjusted R^2 of all of my regressions came out very high, all above 0.93. This is due mainly to the high level of explanatory power present in the total number of carcasses variable. The regressions including district-level fixed effects also explain much of the variability in my dependent variable. This informs my preference for the models including these fixed effects, particularly model (3). This model structure controls for time-invariant, unobserved characteristics within each district I hypothesize could impact the number of elephants poached. For example, overall crime rates are not included in the IPUMS-International dataset, but my fixed effects models account for areas that have higher crime rates on average.

VI. Robustness Checks

Table 5 reports the results of two models (one with district fixed effects, one without) for each of the two alternative dependent variables. First, the district fixed effects model with the dependent variable IllegHT (the number of elephants killed illegally per one hundred thousand people) yields similar results to my preferred model specification. Unemployment still has a significant, positive coefficient, representing a direct relationship between unemployment and the number of elephants killed illegally. The coefficient of 0.962 means that a one percentage point increase in the unemployment rate leads to approximately one more elephant killed illegally per one hundred thousand people in a district. The coefficient on TotHT has a roughly equal magnitude to the coefficient on the total number of carcasses in my preferred model specification, which is a testament to the robustness of that model. The effect of the percent of the population in agriculture is comparable as well. Finally, this model maintains a high R^2 and adjusted R^2. Overall, this model supports the results of the preferred model and alleviates concerns about the analytic sample having lower district populations on average than the overall sample of demographic data. The model using this dependent variable without fixed effects has similar signs to the model (4), but lacks the same level of significance.

Table 5: Robustness Checks Using Alternative Dependent Variables

	Dependent Variable			
Independent Variables	**IllegHT**		**PropIllegal**	
Unemployment Rate	0.962* (0.42)	-0.052 (0.07)	0.0968 (0.11)	-0.0057 (0.01)
TotHT	0.547*** (0.05)	0.582*** (0.03)	-	-
% in Agriculture	-0.268* (0.12)	-0.014 (0.03)	-0.0029 (0.01)	0.0029 (0.01)
% with Less than Primary Education	-0.0698 (0.18)	0.007 (0.03)	-0.0745*** (0.01)	-0.0009 (0.01)
Log(Population)	-	-	0.0042 (0.50)	0.018 (0.12)
District FE	**Y**	**N**	**Y**	**N**
Observations	30	30	30	30
R-squared	0.995	0.960	0.974	0.082
Adjusted R-squared	0.963	0.953	0.811	-0.065
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.				

Conversely, the fixed effect model with PropIllegal as the dependent variable (the proportion of discovered elephant carcasses that were killed illegally) generates very different results from the preferred model. The coefficients on the unemployment rate and the percent of the population in agriculture preserve their signs but lose significance. The logged population remains insignificant. However, in this specification, the percent of the district with less than a primary education appears to have a highly significant, negative effect on the proportion of elephants killed illegally. This would mean that a one percentage point increase in the percent of a district with less than a primary level of education would decrease the proportion of elephants killed illegally. Nevertheless, as previously stated the use of this dependent variable cuts down the variability between different amounts of elephant carcasses that were poached and those which died naturally, resulting in a lower R^2 and adjusted R^2 than the preferred model. The model using PropIllegal as a dependent variable without fixed effects again retains the negative sign on unemployment, as in (4), but is insignificant. Furthermore, this model has an extremely low R^2 and adjusted R^2, further evidence against this choice of model compared to the others.

VII. Limitations

The most notable limitation of my paper is the lack of available demographic data for the districts and years in my analysis. My analytic sample contains only thirty observations with four demographic control variables due to these data availability constraints. The lack of universally available demographic data is particularly problematic in the case of my fixed effects regressions because they only can make use of eight of the districts in the analytic sample. Furthermore, IPUMS-International does not include an income or poverty variable across all the countries included in my analysis, which the literature suggests is an important factor to consider for this topic. The reason this paper is the first to study the effect of unemployment on elephant poaching generally across Africa is most likely due to this significant socioeconomic data limitation across the continent.

Another limitation of my analysis in addressing whether increases in local unemployment rates increase poaching across the African continent is that the MIKE dataset may introduce selection bias. MIKE sites, where these data are collected, are located in natural parks and reserves. These areas likely have better detection capabilities than the areas hosting the remaining 60-70% of the elephant population. Therefore, this dataset might have lower poaching rates than the overall population.

Additionally, my analyses are not able to differentiate between different motivations behind poaching. As previously discussed, African elephants are poached for their ivory, but they are also poached for bushmeat during times of economic hardship and for defending farmland from elephants during instances of human-elephant conflict. I lack a variable to account for the demand for ivory, for example, which would more clearly identify the draw of the illegal ivory trade as an alternative during periods when there is a shortage of other suitable employment opportunities. I also lack variables that account for the age at which an elephant was killed; a younger age at time of death would signal its being harvested for local bushmeat consumption. These severe limitations offer opportunities for future research.

VIII. Future Research

In the future, a more definitive study on the relationship between unemployment and African elephant poaching will require more comprehensive data collection, primarily on the demographic side. The lack of universally available demographic data was the primary constraint for my analytic sample, so future studies could benefit from IPUMS-International gaining access to these data or utilizing a more comprehensive dataset.

In line with the literature on this subject, future research could also access data on the price of ivory, which is collected by The Elephant Trade Information System (ETIS). This variable would act as a proxy for the demand for ivory, which would better identify poaching with the goal of entering the illegal ivory trade. Additionally, data on elephants' ranges across Africa would be helpful, which can be obtained using the African Elephant Database (AED). Future research might also consider including data on the market prices of cattle, goats, maize or other widely distributed goods as proxies for local economic health and/or variables to control for local environmental conditions that may impact the number of elephants poached, such as droughts. Lastly, data on changes in policies and laws which adjust the penalties for or detections of poachers would strengthen this type of analysis considerably. While this paper contributes some evidence towards the validity of the relationship between changes in the unemployment rate of districts and the rate of poaching, its limitations imply ample room for improvement in future research.

IX. Conclusion

Considering the very small sample size of my analytic dataset, it is promising that I see any statistically significant results of unemployment impacting poaching rates. Even with my data limitations, I contribute evidence supporting that an increased level of unemployment within a district increases the number of elephants poached. Specifically, I estimate a one percentage point increase in the unemployment rate to correspond to approximately 3 to 4.5 more poached elephants within a given district. This result may not seem particularly large, but when multiplied out across all the districts within the African nations where elephants live, fighting unemployment could have a significant beneficial effect for elephant populations across the continent.

My analysis does not lend evidence of increases in unemployment increasing the number of poached elephants across districts, but rather that they *decrease* the overall number of elephants poached. Across districts, I find that a ten percentage point increase in the unemployment rate leads to roughly three fewer poached elephants. The diverging results between my regressions including and excluding district fixed effects suggest further research is needed on the unobserved differences between districts.

The results of this paper have important policy implications. Strategies against elephant poaching which only increase the severity of punishments for those caught poaching or the detection of poachers will not address how it serves as an alternative labor market opportunity for the unemployed. There are examples from the nonprofit sector of organizations that have been able to provide jobs while also preserving African elephant populations. One such nonprofit provides jobs to members of the community rescuing and rehabilitating elephants orphaned as the result of various circumstances, including poaching (Sheldrick Wildlife Trust, n.d.). This is merely one example of how alternative employment opportunities provided through the nonprofit sector can encourage African elephant conservation, but the scale necessary to protect the species will likely require the cooperation of the private and public sectors as well.

While this paper focuses on how local economic conditions impact the rate of African elephant poaching within a district, these results may reveal a theme for other types of wildlife trafficking as well. Future research must test this hypothesis in different contexts, for different species and/or nations. Under Becker's framework (1968), it is reasonable that unemployment within a region, especially in a developing nation without a strong social safety net, would contribute to the rate of illegal wildlife poaching. Considering biodiversity conservation as a normal good, improving local economic conditions will likely dissuade people from participating in wildlife trafficking. However, the threat to the African elephant, and to other species which share in its turmoil, is highly time-sensitive, and a nation's economic development is clearly not a quick process. While other policies and initiatives are likely needed to ensure the short-term survival of species jeopardized by poaching, economic development and strengthening employment opportunities may be the best path to their survival in the long run.

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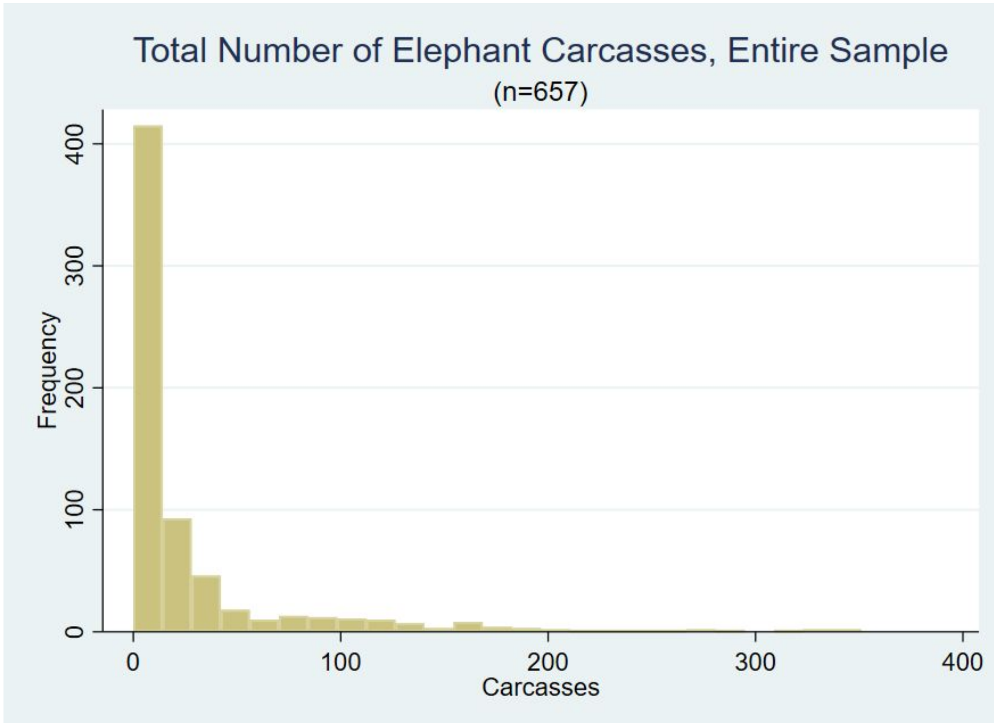
A. Appendix

Table A.1: Geographic Breakdown of the Analytic Sample

Region	Country	District	Observations
Central Africa	Cameroon	Est	1
		Nord Ouest	1
Eastern Africa	Rwanda	East	1
	Tanzania	Katavi	2
		Manyara	2
		Morogoro	2
		Singida	2
		Tanga	1
	Uganda	Western	1
Southern Africa	Malawi	Central	1
	Mozambique	Gaza	1
		Niassa	1
		Tete	1
	South Africa	Mpumalanga	2
	Zambia	Eastern	2
		Lusaka	1
		Northwestern	1
West Africa	Benin	Alibori	2
		Atacora	2
	Ghana	Central	1
		Northern	1
	Mali	Tombouctou	1

Figure A.1: Histogram of Total Number of Carcasses for Each Sample



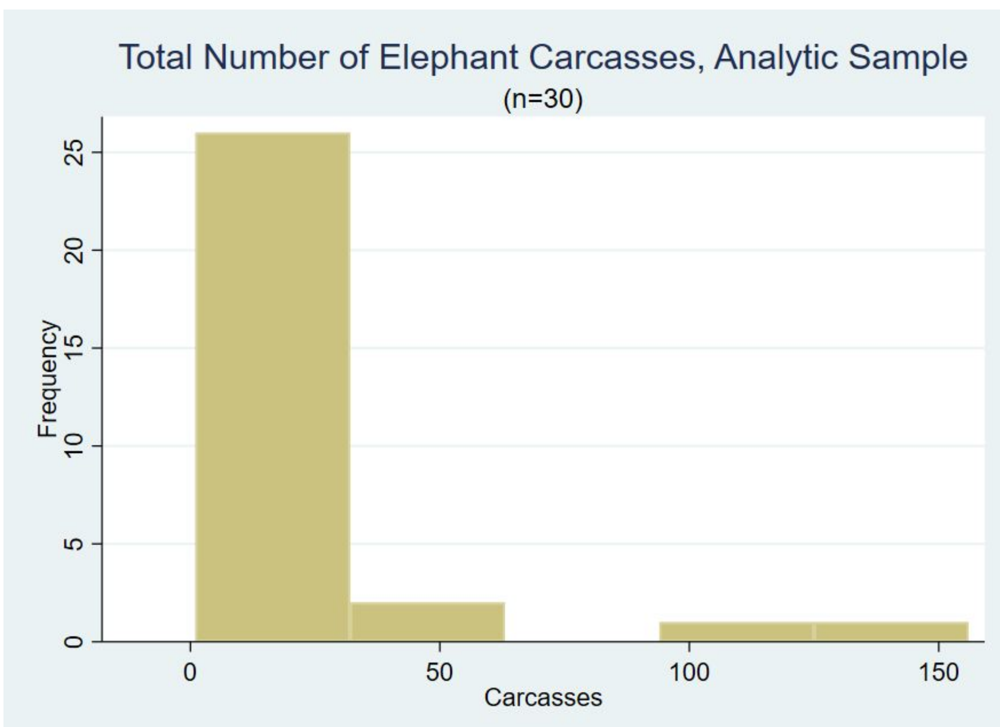
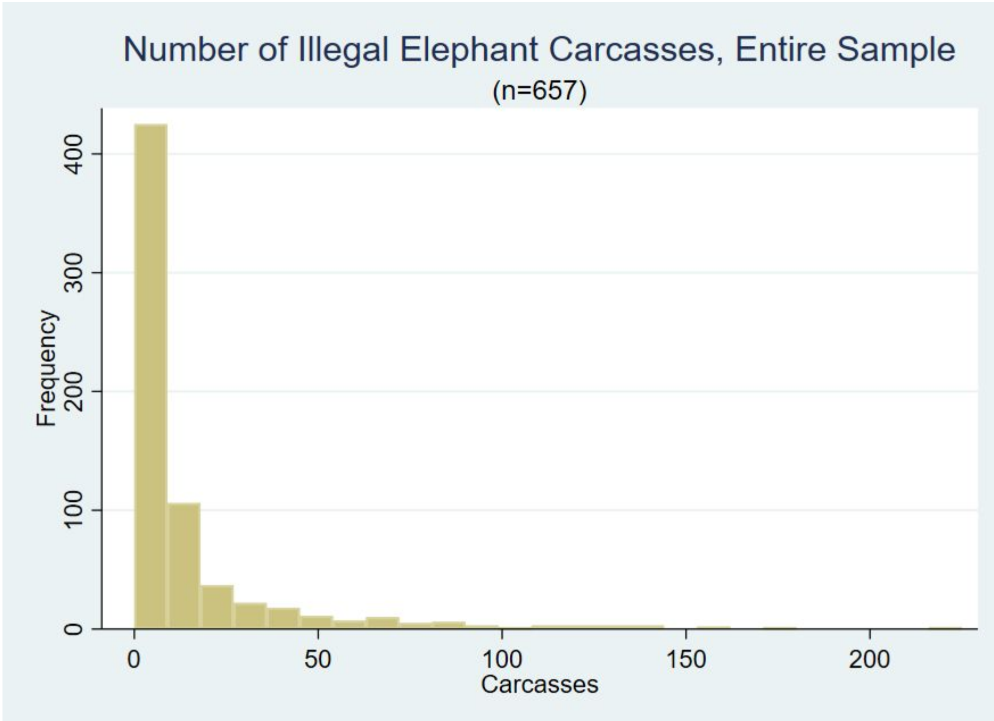


Figure A.2: Histogram of Illegal Carcasses for Each Sample



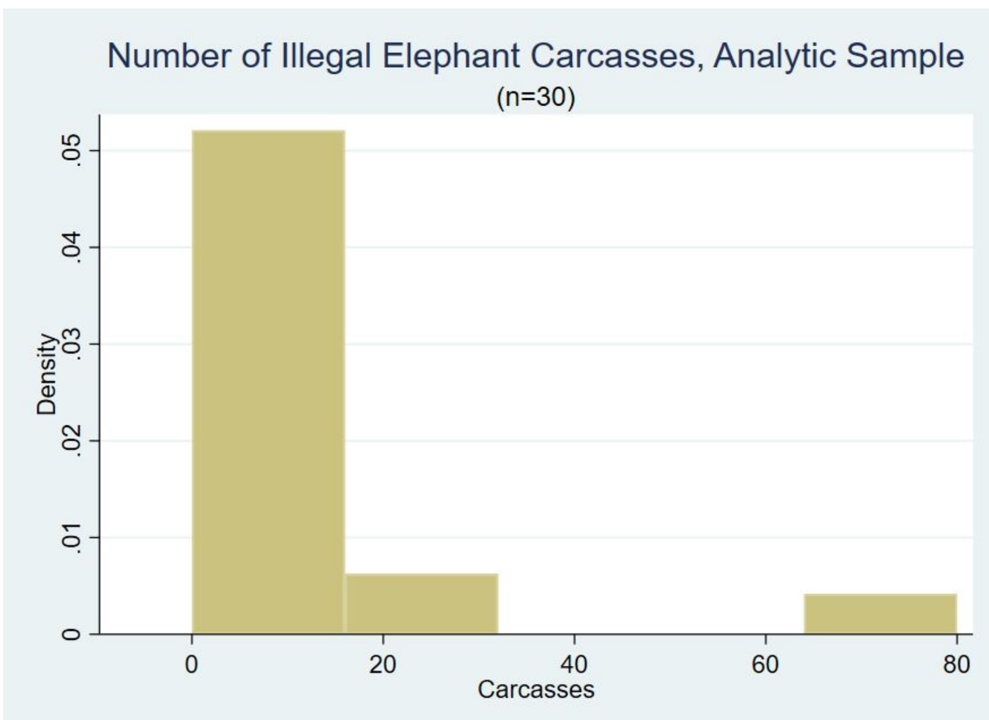


Figure A.3: Percent of Total Carcasses Discovered by African Subregion for Each Sample

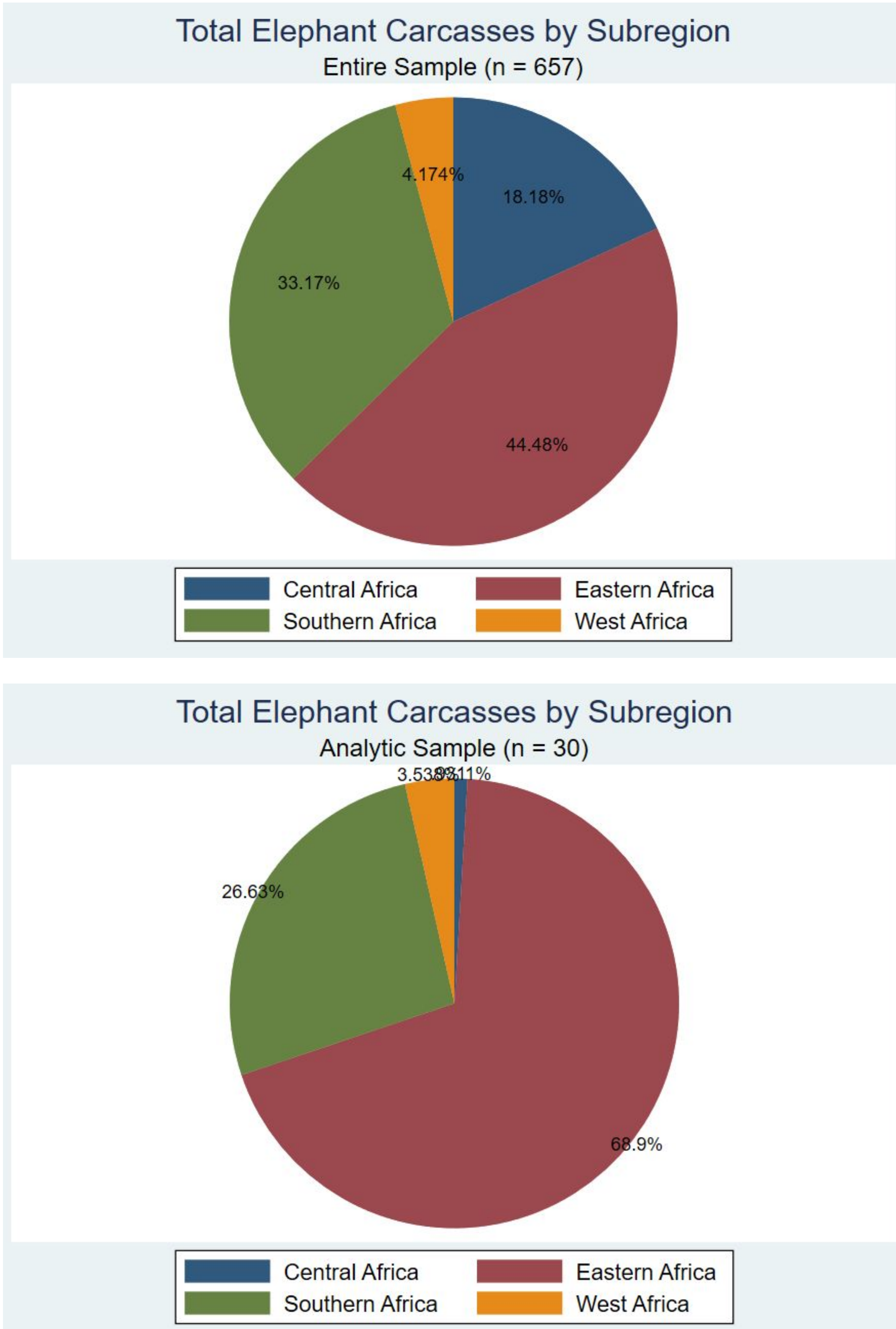


Figure A.4: Percent of Illegal Carcasses Discovered by African Subregion for Each Sample