A Drought-Induced African Slave Trade?

Boxell, Levi

Stanford University

3 March 2016

A Drought-Induced African Slave Trade?*

Levi Boxell[†]

Stanford University

First Version: June 6, 2015
This Version: March 4, 2016

Abstract

Historians have frequently suggested that droughts helped facilitate the African slave trade. By introducing a previously unused dataset on historical rainfall levels in Africa, I provide the first empirical answer to this hypothesis. I demonstrate how negative rainfall shocks and long-run shifts in the mean level of rainfall increased the number of slaves exported from a given region and can have persistent effects on the level of development today. Using a simple economic model of an individual's decision to participate in the slave trade, along with observed empirical heterogeneity and historical anecdotes, I argue that consumption smoothing and labor allocation adjustments are the primary causal mechanisms for the negative relationship between droughts and slave exports. These findings contribute to our understanding of the process of selection into the African slave trade and have policy implications for contemporary human trafficking and slavery.

JEL Classification: N37, N57, O15, Q54

Keywords: slave trade, climate, droughts, consumption smoothing, human trafficking

*Acknowledgments: I would like to thank Jiwon Choi, John T. Dalton, James Fenske, Matthew Gentzkow, Namrata Kala, Andres Shahidinejad, Jesse M. Shapiro, and Michael Wong for their comments and suggestions. All remaining errors are mine.

[†]SIEPR, Stanford University (Email: lboxell@stanford.edu)

1 Introduction

The African slave trade significantly altered modern economic and cultural outcomes (Nunn, 2008). Areas that exported more slaves tend to be less trusting, display increased ethnic stratification, have lower literacy rates, and have an increased prevalence of polygyny (Nunn and Wantchekon, 2011; Whatley and Gillezeau, 2011; Obikili, 2015; Dalton and Leung, 2014). What caused certain regions to export more slaves than others? While the impact of the African slave trade is well documented, there have been few empirical investigations into the supply-side determinants of the slave trade.[1]

On the other hand, the historical literature is dense with speculation on what contributed to the rise of the slave trade in certain regions. One particular discourse surrounds the role of droughts.[2] Historians suggest that Africa suffered a prolonged dry spell from 1630 to 1860, which helped facilitate the growing slave trade (Brooks, 2003, 102-3). In addition to attributing the growth of the slave trade to shifts in the mean level of rainfall, historians also attribute spatial and temporal variations in the slave trade to short-run fluctuations in rainfall. This connection is made in geographically dispersed areas — from Senegambia to Angola to Mozambique (Curtin, 1975; Miller, 1982; Newitt, 1995). Periods of drought are thought to have increased the number of slave exports due to increased conflict, people selling themselves into slavery, and migration that left populations vulnerable (Lovejoy, 2012, 29). However, not all historians follow this line of thought. Zeleza (1997, 34) calls these previous claims "an inept attempt to 'blame' the slave trade on nature and the victims themselves."

The closest related empirical study is Fenske and Kala (2015). They find a negative relationship between temperature shocks and slave exports. They explain their results by modeling the decisions of a coastal ruler who maximizes his profit by varying the number of slave exports based upon the climate-induced changes in explicit costs. They argue that the impact of agricultural yields on the explicit costs of the slave trade is the primary mechanism for the negative relationship between temperature and the slave trade. Contrary to the dominant hypothesis proposed by historians, their model and proposed mechanism suggest that periods of drought would similarly decrease the number of slaves exported from a given region. Fenske and Kala (2015) only study temperature anomalies, as they note the absence of rainfall data for the 1730 to 1866 time period. However, historically reconstructed data on rainfall anomalies does exist from 1801 to the present (Nicholson, Dezfuli and Klotter, 2012). To the best of my knowledge, this data has not been used outside of the climatology literature.

I use this data to provide a direct empirical answer to the debate on the role of droughts in the African slave trade. I find that negative rainfall shocks substantially increased the number of slaves exported from the region experiencing the shock. Specifically, a one standard deviation decrease in the previous year's rainfall is estimated to increase annual slave exports from a port by roughly 460 slaves. In addition to rainfall shocks, long-run trends in the mean rainfall level also display a negative relationship with the number of slaves exported from a port. In parallel, I also examine the robustness of the negative relationship between temperature and the slave trade to the inclusion of rainfall. While my baseline model confirms the negative relationship between temperature and the slave trade, I find that the relationship is sensitive to the specification used. On the other hand, the negative relationship between rainfall and the slave trade is relatively stable across robustness checks.

To explain my findings, I expand on the model developed within Fenske and Kala (2015). In West Africa, approximately half of the variance in precipitation is low-frequency variance with persistence of seven years or more. Other regions of Africa show similar, but less persistent, patterns (Nicholson, 2000).

[1] Nunn and Puga (2012), Whatley (2014), and Fenske and Kala (2015) are exceptions.

[2] An in-depth review of the historical context of slavery in pre-colonial Africa is beyond the scope of this paper and can be found elsewhere (Lovejoy, 2012; Nunn, 2008).

We can expect rational agents to adjust the allocation of their factors of production to take advantage of the long-run shifts in productivity and costs induced by climate trends. Furthermore, the negative income shocks associated with a lack of rainfall can motivate various consumption smoothing strategies. One strategy available is increased specialization in the slave trade. This specialization includes selling household members into slavery, kidnapping, and conflict. Acknowledging these phenomena, I allow individuals to choose their degree of specialization between agriculture and the slave trade based on the opportunity costs of the two industries. By incorporating this additional feature, I am able to explain the empirical results for both the negative relationship between rainfall and slave exports and the negative relationship between temperature and slave exports. The model suggests that rainfall shocks operate through the opportunity cost mechanism, while temperature shocks operate through the explicit cost mechanism.

In addition to being explained by the theoretical model, the heterogeneity of rainfall's impact on the slave trade also supports the opportunity cost interpretation. I find the negative relationship between rainfall and slave exports to be strongest in regions where incomes are more closely correlated with rainfall shocks, as proxied by various agricultural and climactic measures. The historical anecdotes from the African slave trade also corroborate my proposed mechanism. Using Angola as a case study, I show how long-run precipitation trends during the slave trade pushed certain groups, such as the Imbangala, to shift labor allocation between the slave trade and agriculture. Furthermore, numerous Angolan anecdotes relate short-run precipitation shocks to desperate consumption smoothing strategies that include selling family members into slavery at substantially reduced prices.

I also show how rainfall-induced changes in the number of slave exports can have long-run impacts on the level of development today. Areas that were abnormally dry during the study period have lower levels of average night-time light intensity. The level of rainfall in the 19th century is a plausibly exogenous source of variation to the level of slave exports from Africa. Besides through the slave trade, it is unlikely that rainfall in the 19th century impacts contemporary economic outcomes after controlling for contemporary climate conditions. This provides an additional robustness check to previous findings on the long-run impact of the slave trade on Africa's development.

1.1 Related Literature

The trans-Atlantic slave trade was a collaborative effort between the Americas, Europe, and Africa. On the European-side, the literature has examined, among other topics, the importance of managerial ability, market distortions, and the 1807 British Slave Trade Act in contributing to the temporal and spatial variation in slave exports (Dalton and Leung, 2015*a*,*b*; Lovejoy and Richardson, 1995). On the African-side, previous studies have emphasized geography and the gun-slave cycle as determinants of the level of slave exports from a given region (Nunn and Puga, 2012; Whatley, 2014). Within this literature, I contribute to the understanding of the process of selection into the slave trade by showing how rainfall shocks and trends influenced the degree to which a region participated in the slave trade. This confirms the importance of environmental factors in the African slave trade (Fenske and Kala, 2015). I also provide a more complete model of the mechanisms through which climate conditions interacted with the slave trade by accounting for both explicit and opportunity costs.

This paper also relates to a large literature on consumption smoothing by poor households in response to income shocks (Morduch, 1995; Jappelli and Pistaferri, 2010). Low-income societies often lack formal credit markets to smooth consumption patterns. This leads to the use of informal consumption smoothing strategies. One strategy available is shifting labor allocation. For example, farmers in developing countries smooth consumption by increasing non-agricultural labor allocation in response to lower commodity prices (Adhvaryu, Kala and Nyshadham, 2015). Another consumption smoothing strategy is the sale and manipulation of human assets. There has been a growing literature on the use of marriage as a consumption smoothing strategy in cultures where bride prices are prominent (Hoogeveen, Klaauw and Lomwel, 2011; Corno and Voena, 2015). In cultures with dowries, violence against women tends to increase during adverse weather shocks in an attempt to extract further dowry payments (Sekhri and Storeygard, 2014). Women in low income societies also tend to migrate to different regions for marital purposes. This migration effectively operates as family insurance against region-specific weather shocks (Rosenzweig and Stark, 1989). I contribute to this literature by demonstrating how historical African societies sold household members and shifted labor allocations towards the slave trade in response to negative income shocks.

Another related strand of literature is on human trafficking. In general, the economic literature on human trafficking is lacking. The few theoretical papers that exist focus on the relationship between migration and trafficking (Tamura, 2010; Djajić and Vinogradova, 2013; Joarder and Miller, 2013). Empirical studies are limited in their ability to draw conclusions due to an absence of sufficient data. The studies that have been done either emphasize the importance of migratory flows and migrant networks in determining the level of human trafficking in a region (Mahmoud and Trebesch, 2010; Cho, 2015) or examine the impact of legalized prostitution on reported human trafficking inflows (Cho, Dreher and Neumayer, 2013). The African slave trade provides a valuable historical archive of information from which economists and policymakers can learn, as the contemporary and historical slave trades share many similarities (Patterson, 2012). I contribute to the literature by demonstrating how consumption smoothing can motivate self-selection into the historical slave trade and, by parallel, into modern human trafficking. Furthermore, by studying the relationship between droughts and the historical slave trade, I provide a framework to begin understanding the potential impacts of climate change on human trafficking today. The results suggest a stark reality. As climate change increases the frequency of droughts, consumption smoothing efforts may contribute to an increased prevalence of human trafficking.

The rest of the paper is outlined as follows. Section 2 explains the data, section 3 gives the main empirical results, section 4 examines the potential mechanisms within the historical context of the slave trade, and section 5 concludes.

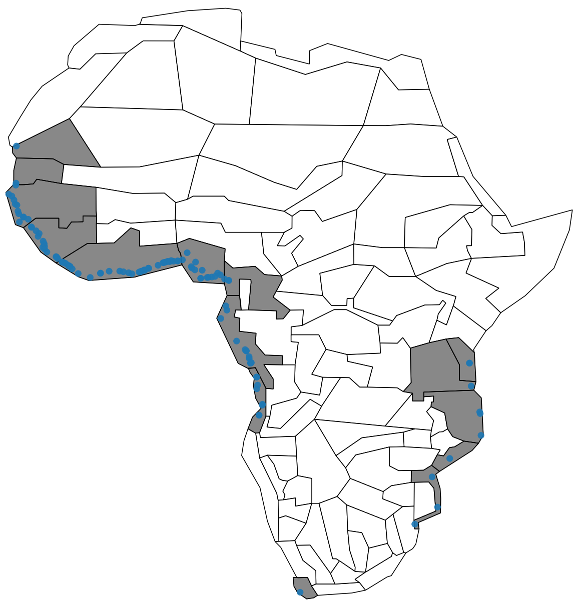
2 Data

2.1 Rainfall

The dataset on rainfall anomalies comes from Nicholson, Dezfuli and Klotter (2012) and is stored at the National Oceanic and Atmospheric Administration's World Data Center for Paleoclimatology.[3] This dataset is previously unused in the economic literature, but provides a valuable resource for understanding how the climate impacted pre-colonial and colonial Africa. To construct the historical values, the continent is first partitioned into homogeneous rainfall regions, which were introduced by Nicholson (1986) and can be seen in Figure 1. The regions are constructed using spatial and temporal variations in rainfall from 1901 to 1973. Areas with highly correlated temporal variation in rainfall are denoted homogeneous regions.

[3] The original data can be found at <https://www.ncdc.noaa.gov/cdo/f?p=519:1:394453854382201::::P1_STUDY_ID:12201>.

Figure 1: Homogeneous Rainfall Zones and Ports



Notes: The grey regions are the homogeneous rainfall regions used in the study. The blue dots are the ports.

The key idea from these homogeneous regions is that information about rainfall from any point within the region can be used to describe rainfall across the entire region with a relatively high degree of accuracy. This allows for the reconstruction of historical rainfall values for each year from 1801 to 1900. The data is reconstructed using a combination of rain gauge data, written historical descriptions, and spatial interpolation. The use of written and visual primary sources prevents the measurement of rainfall in inches or centimeters per year. Therefore, Nicholson, Dezfuli and Klotter (2012) use a seven-tier rating system that describes the amount of rainfall in a given year. Table 1 gives the different levels and their description.

When gauge data is available, it is used and assigned a value based upon the variation in the data. If gauge data is not available, a wide variety of sources are utilized. These include the writings of explorers, settlers and missionaries, local oral and written tradition, and hydrological records of lakes and rivers. Missing values are imputed using a combination of linear interpolation and spatial imputation. I then assign each port the rainfall value for the region in which it is located after subtracting the region's mean rainfall level between 1801 and 1866.[4]

2.2 Temperature

For temperature data, I utilize a dataset constructed in a manner similar to the rainfall dataset. Using a wide variety of proxy and instrumental climate indicators and calibrating the model on known data, Mann, Bradley and Hughes (1998) develop a $5° \times 5°$ global grid of temperature anomalies. I follow Fenske and Kala (2015) by using a bilinear interpolation of the four nearest temperature points for each port.[5] As done for the rainfall variable, I also take the difference between a given year's temperature

[4]Empirically, this demeaning makes little to no difference when port fixed effects are included. However, it allows the descriptive statistics to give a truer picture of the underlying variation and helps account for any systematic differences in the historical reconstruction across regions when port fixed effects are excluded.

[5]More detailed explanations of the data construction can be found within Fenske and Kala (2015) and at `<http://www.ncdc.noaa.gov/paleo/pubs/mann1998/frames.htm>`.

value and the mean temperature value for each port between 1801 and 1866.

Measurement error is prominent with paleoclimate reconstructions. Furthermore, monthly or seasonal data would be preferable due to the differential impacts of climate on agriculture throughout the year. However, as long as the measurement error is uncorrelated with slave exports, the error will merely attenuate the coefficient estimates and bias the standard errors upwards. Since the null hypothesis is that rainfall and temperature have no impact on slave exports, both of these biases suggest my results are conservative.

2.3 Slave Exports

The data on slave exports originally come from Eltis et al. (1999). Slaves exported from a known port are assigned to that port. Slaves exported from a known area, but unknown port, are assigned proportionally to the ports in the area based upon the known exports in the same year. Slaves exported from an unknown area and unknown port are assigned proportionally to all ports based upon the known exports for that year.[6] I then restrict my sample to those ports covered by a rainfall region.[7] This gives 123 ports.

The average slave exporting port in the sample exported roughly 410 slaves annually, as shown in Table A1. To give a rough sense of the the temporal dynamics of slave exports for this time period, I plot the total slave exports from a given rainfall region in Figure A4. This time period contains roughly 25 percent of the estimated 12 million slaves exported from Africa between 1501 and 1866. Later, I examine the sensitivity of my results to the study's time period.

2.4 Climate and Agriculture

I also utilize data on the agro-ecological zones (AEZ), dominant agricultural crop, and malaria suitability of each region. The spatial distribution of these variables can be seen in Figures A7 – A9. The data for the AEZ zones comes from the Food and Agricultural Organization. There are five zones used: desert, sub-humid, humid forest, dry savannah, and moist savannah.[8] Each port is assigned the AEZ zone of the closest administrative unit, as done by Kala, Kurukulasuriya and Mendelsohn (2012). The data on the dominant crop and type of agriculture comes from Murdock (1967) and is assigned at the ethnic level. There are four different crop types: cereals, roots, trees, and none. Each port is assigned the most frequently dominant crop of the ethnic zones within 500 km of the port or the nearest society if none are listed within 500 km. Table A1 shows that the most common crop is cereals and the most common AEZ zones are dry savannah and humid forest.

Malaria suitability comes from the Malaria Atlas Project (`http://www.map.ox.ac.uk/map/`). The variable is constructed by taking the average value within a 500 km buffer of each port and normalizing it to have a mean of zero and standard deviation of one across ports.

3 Empirical Model and Results

The main empirical model is

[6] I utilize the cleaned data set of this format provided by Fenske and Kala (2015).

[7] I include ports that are roughly within 75 km of mainland and assign them the rainfall value of the nearest rainfall region. The closest port excluded is "Fernando Po" or present-day Malabo. See the online appendix for more details on the port sample.

[8] A sixth AEZ zone exists, semi-arid, but is ignored due to the lack of observations.

Table 1: Non-linearity of Rainfall?

Variable	Description	Slave Exports Coefficient	SE
Rain Level$_{t-1}$			
-3	Severe drought; Causes famine and/or migration	415.3	(422.6)
-2	Drought	-120.3	(318.3)
-1	Dry	-298.5	(414.8)
0	Average	0	–
1	Wet	-615.7	(485.0)
2	Anomalously wet	-1960.1***	(508.0)
3	Severe Rainfall; Typically causes flooding	-606.6	(470.4)
Temp$_t$		-1912.0	(1456.7)

Notes: Tobit regression with port fixed effects, year fixed effects, and 7995 observations. Dependent variable is the number of slaves exported from a port in a given year. Standard errors are clustered by rainfall region.
* $p < .1$, ** $p < .05$, *** $p < .01$

$$\text{Slaves}_{it} = \max\left(0,\ \delta_i + \eta_t + \text{Rain}_{i,(t-1)}\beta + \text{Temp}_{it}\gamma + \epsilon_{it}\right),$$

where Slaves_{it} denotes the amount of slaves exported from port i at time t, $\text{Rain}_{i(t-1)}$ is a, possibly vector valued, representation of the previous year's rainfall, Temp_{it} denotes the contemporary temperature anomaly, δ_i is a port-specific fixed effect, and η_t is a year-specific fixed effect.[9] Since Slaves_{it} is constrained to be non-negative, $\text{Slaves}_{it} = 0$ represents a corner solution. Typical OLS regressions are inconsistent under these assumptions (Wooldridge, 2002, 524-5). This leads to the use of a type-I Tobit model. The main parameters of interest are β and γ whose identification comes from the exogenous variation in rainfall and temperature shocks across regions after controlling for unobserved port-specific heterogeneity and temporal changes in the slave trade.

Out of concern for non-linearity, I initially model the impact of rainfall on slave exports by creating an indicator variable for each of the seven rainfall levels. Non-linearity in the temperature variable is of less concern, as temperature has an approximately linear impact on agriculture (Kurukulasuriya and Mendelsohn, 2008) and, while nonlinear, the disease burden is monotonically increasing in temperature (Alonso, Bouma and Pascual, 2011). As such, I use the temperature variable described in the data descriptions. Table 1 shows that the impact of rainfall on slave exports is approximately linear with the only significant anomaly being the rainfall level that typically corresponds with flooding conditions. This result motivates the use of a single variable denoting the port-demeaned rainfall level along with a flood indicator variable, which takes on the value of one when the port-demeaned rainfall level is greater than three.

Using this specification, my main result in Column (1) of Table 2 shows that the coefficient on rainfall is negative and significant at the one percent level. Specifically, a one level (standard deviation) decrease in a port's rainfall in the previous year is estimated to cause approximately 290 (460) more slaves to be exported from the port. This result confirms the hypothesis proposed by various historians of the trans-Atlantic slave trade that droughts increased slave exports (Curtin, 1975; Newitt, 1995; Brooks, 2003; Lovejoy, 2012). When controlling for temperature shocks, the coefficient on rainfall is relatively unchanged as shown in Column (3) of Table 2. The negative coefficient on temperature shocks

[9]The temporally lagged rainfall shock may appear arbitrary. However, I explore various lags in Figure A11 and only the first lag is significant for rainfall. The temporal lag on rainfall is also consistent with the temporal lag found by Crost et al. (2015) for the impact of rainfall on civil conflict when operating through agricultural production.

Table 2: Main Results

	Slave Exports				log(Light Intensity)
	(1)	(2)	(3)		(4)
Rain_{t-1}	-288.2***		-280.3***	Weighted Rain	0.562*
	(85.06)		(78.49)		(0.305)
Flood_{t-1}	1218.6*		1158.8*	Weighted Flood	-0.335
	(640.0)		(640.9)		(0.572)
Temp_t		-1608.1	-1394.6	Weighted Temp	0.630***
		(1637.7)	(1509.3)		(0.197)
Port F.E.	Yes	Yes	Yes	Controls	Yes
Year F.E.	Yes	Yes	Yes		
Obs.	7995	8118	7995	Obs.	123

Notes: Columns (1) - (3) use Tobit regressions with standard errors clustered by rainfall region in parentheses. Column (4) uses OLS with standard errors clustered by rainfall region in parentheses. Control variables include malaria suitability, presence of petroleum, distance to nearest foreign port, number of raster light intensity points within 500 km, AEZ zone, absolute latitude, longitude, average temperature, and average rainfall level.
* $p < .1$, ** $p < .05$, *** $p < .01$

corroborates the findings of Fenske and Kala (2015) and suggests that their main result is robust, at least in sign, to the inclusion of rainfall shocks, though it is not significant at conventional levels.

The impact of climate conditions on slave exports is not limited to shocks, but long-run trends also impact the level of slave exports. The climate of the region surrounding a port can be thought of as a probability distribution $D(\mu, \omega)$ with mean μ and variance ω. Each year, a draw is taken from the distribution. The previous regressions in Table 2 assume that the mean of the distribution is constant across the entire time period. However, climate change could result in a new distribution $D(\mu', \omega')$ with new mean μ' and variance ω'. To examine the impact of climate changes, I let Rain Trend_t (Temp Trend_t) denote the lagged moving average of Rain_t (Temp_t) and let Rain Shock_{t-1} (Temp Shock_t) denote the previous (contemporary) year's deviation from Rain Trend_t (Temp Trend_t). The moving average is a proxy for the distribution's mean. I use moving averages of length 5, 10, and 20 years.

As reported in Table 3, the coefficients on Rain Trend_t and Rain Shock_{t-1} are both negative for all moving averages, though with varying statistical significance. Using the standard deviations reported in Table A1, we see that a one standard deviation change in Rain Trend_t has a substantially larger impact than a one standard deviation change in Rain Shock_{t-1} for the 5-year and 10-year moving averages, but they are approximately equal for the 20-year moving average. This is consistent with individuals using previous climate draws to update their priors about the contemporary climate distribution and adjusting their factors of production accordingly. As the length of the moving average increases past a certain point, the information about the contemporary climate distribution is diluted, and so Rain Shock_{t-1} is given more weight in the decision making process.

The coefficients on Temp Shock_t and Temp Trend_t are also negative when examined together for all moving averages, though Temp Trend_t is statistically insignificant throughout and even positive when excluding Temp Shock_t. Furthermore, we see that the relative impact of a one standard deviation change is much larger for Temp Shock_t and, while imprecisely estimated, the magnitude of a one standard deviation change in Temp Trend_t is close to zero. This suggests that the impact of temperature on slave exports may be operating through different mechanisms than for rainfall.

I also examine the persistent impact of climate anomalies during the 19th century slave trade on

Table 3: Trends and Shocks

	Dependent Variable: Slave Exports					
	5 Year MA		10 Year MA		20 Year MA	
	(1)	(2)	(3)	(4)	(5)	(6)
Rain Trend$_t$	-461.6**	-473.6**	-746.8**	-724.3**	-826.0	-800.4
	(188.3)	(191.5)	(311.6)	(319.3)	(688.1)	(649.3)
Rain Shock$_{t-1}$		-90.6*		-99.54		-227.7**
		(50.44)		(87.72)		(98.19)
Temp Trend$_t$	-485.0	-2376.2	1758.7	-767.9	5956.5	-592.0
	(1718.0)	(1998.7)	(3487.4)	(2876.4)	(12882.4)	(11002.1)
Temp Shock$_t$		-2420.5		-2494.8*		-3371.3
		(1546.1)		(1505.4)		(2091.9)
Port F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7503	7380	6888	6765	5658	5535

Notes: Tobit regressions with standard errors clustered by rainfall region in parentheses. 'Rain Trend$_t$' is a moving average of the previous rainfall levels. 'Rain Shock$_{t-1}$' is the deviation from the moving average in the previous year.

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

modern outcomes using night-time light data from Henderson, Storeygard and Weil (2012) as a proxy for development. Each port is assigned the average light intensity for the area within 500 km of the port in 2009. I use a weighted sum of the anomalies for each port, i, in the following fashion:

$$\text{Weighted Rain}_i = \sum_t \frac{\text{Slaves}_t \times \text{Rain}_{i(t-1)}}{\sum_t \text{Slaves}_t}$$

where Slaves_t represents the total exports from all ports in a given year. I use OLS to estimate the persistent impact of these weather anomalies on the log of light intensity. Control variables include malaria suitability, presence of petroleum, distance to nearest foreign port, number of raster light intensity points within 500 km, AEZ zone, absolute latitude, longitude, average temperature, and average rainfall level. Column (4) of Table 2 shows that positive rainfall shocks during the 19th century slave trade are correlated with an increase in the level of development today. This corroborates previous studies, such as Nunn (2008), which demonstrate the persistent impact of the historical African slave trade on modern outcomes.

3.1 Robustness

Beyond including the impact of temperature, I perform various robustness checks to ensure the main relationship holds. All robustness checks are reported in Table A2. In general, the negative relationship between rainfall and slave exports is stable, while the coefficient on temperature is more sensitive to changes in specification.

3.1.1 Measurement

First, I test the sensitivity of my results to the geographic level of aggregation by changing the level of aggregation of slave exports to the region level. The results suggests that a negative rainfall or temperature shock in a region increases the number of slaves exported from across the entire region. The coefficients on both climate indicators are insignificant at conventional levels, which is to be expected with the reduced sample size. I also perform many of the other regressions reported in this paper at the region level and find my results are similar in sign, but not significance, to those at the port level. These region level results can be found in the online appendix.

Out of concern for potential systematic measurement errors in the mean and variance of the climate indicators across ports, I normalize the rainfall and temperature variables in each port by dividing by the standard deviation of each variable in the given port across the entire sample time period.[10] While the negative coefficient on the temperature variable is not robust to this re-scaling, the coefficient on the rainfall variable remains negative and significant. I also transform the slave exports variable by using $\text{Log}(1 + \text{Slaves}_{it})$. The coefficient on Rain_{t-1} suggests a one level decrease in rainfall increases slave exports by roughly five percent and is significant at the five percent level. The coefficient on temperature is positive and insignificant.

3.1.2 Sample Restrictions

Another issue may be the time period examined. If West Africa exhibited excess rainfall or West-Central Africa exhibited a drought that coincided with the British abolition of the slave trade in 1807, the relationship between rainfall and slave exports could be coincidental, as the major slave exporting ports shifted south after the British abolition. To test this hypothesis, I restrict my sample to various decades. The results show no evidence that the British abolition is driving the results. In fact, the 1801 to 1810 decade is the only decade in which the coefficient on rainfall is positive, but statistically insignificant from zero. The coefficient on temperature fluctuates across decades between negative and positive values, though only the negative coefficients are significant at conventional levels.

I also restrict the sample to various geographic regions — West, West-Central, and East Africa — as defined by Figure A10. Temperature has a consistently negative, but statistically insignificant, relationship with slave exports across the different regions. For rainfall, the coefficient is large and statistically significant at the one percent level for West-Central Africa. On the other hand, the coefficient on rainfall in West Africa exhibits a smaller and insignificant negative relationship, while East Africa actually exhibits a large and statistically significant positive relationship. The results suggest that the interaction between rainfall and slave exports during this time period is being primarily driven by ports in West-Central Africa and the slave trade in Africa may operate under different mechanisms between West and East Africa. During this time period, the West-Central portion of Africa was the main producer of slaves and East Africa had a limited role, as depicted by Figure A5. The sex ratio of exported slaves was also different between East and West Africa, with East Africa exporting a higher ratio of females (see Dalton and Leung (2014) and references therein).

I also restrict the sample to high-export ports (i.e., ports which exported more than 22,000 slaves during the time period) and low-export ports (i.e., ports which exported less than 100,000 slaves during the time period). Both of these regressions exhibit negative and statistically significant coefficients on rainfall, while the coefficients on temperature are negative, but statistically insignificant.

[10] Recall that the variables are already normalized to a within-port mean of zero.

3.1.3 Specification and Estimation

When removing the flood indicator variable, the rainfall coefficient is still large, negative, and significant. I also use OLS to estimate the model for port-years with positive slave exports and conditional logit fixed effects to estimate the model with an indicator variable for positive slave exports. For both models, the rainfall coefficient maintains the same sign as in the Tobit model and is significant at conventional levels. The temperature coefficient on both models is negative, but still not statistically significant. I also estimate the OLS model on the sample of port-years with positive slave exports using first differences to account for the long time series panel. For this regression, both the rainfall and temperature variables are negative and significant at the five and one percent levels, respectively.

I also replace the time fixed effects with port-specific linear and quadratic time trends in the OLS model for port-years with positive slave exports.[11] The coefficient on both rainfall and temperature remains negative, though at attenuated levels. When linear and quadratic time trends along with year fixed effects are included, the estimated impact of both temperature and rainfall increases along with the statistical significance. This suggests that flexibly controlling for annual shocks is important.

Another potential issue is the incidental parameter problem for fixed effects estimation in Tobit models. Greene (2002) shows that the incidental parameter problem primarily impacts the standard error estimates and that the bias decreases as time increases. In his simulations, Greene demonstrates that, with 20 time periods, the remaining bias is trivial for most applications. As I use over 60 time periods, the incidental parameter issue should be of little concern. However, Wooldridge (2002, 542) suggests using the port-specific mean for the climate variables instead of fixed effects as one potential solution to the incidental parameter problem. The rainfall coefficient on this regression maintains a similar magnitude and significance to the coefficient of my main result in Table 2. The temperature coefficient remains negative and insignificant.

Finally, I use a nonparametric bootstrap to estimate standard errors on the main Tobit model at both the region and the port level. While the region aggregation is insignificant for both temperature and rainfall, the port aggregation is significant at the one percent level for rainfall and insignificant for temperature.

4 Mechanisms

4.1 Economic Model

To explain the relationship between climate shocks and slave exports, I develop a model within the spirit of Fenske and Kala (2015). However, I deviate by incorporating rainfall shocks and allowing for the opportunity cost of participating in the slave trade.

Consider an individual (possibly a coastal ruler, representative agent, or head of household) who must choose the degree of specialization between the slave trade and agriculture to maximize economic profit. The individual is faced with the following maximization problem:

$$\underset{S\geq 0}{\operatorname{argmax}}\ P(S)S - C(S,T,R) - F(S,T,R), \tag{1}$$

where $P(S)$ is the price for selling S slaves, $C(S,T,R)$ is the explicit cost of acquiring and selling S slaves

[11] I do not do this for the Tobit model because of convergence issues.

given rainfall R and temperature T conditions, and $F(S,T,R)$ is the opportunity cost of acquiring and selling S slaves given rainfall R and temperature T conditions. Here, S effectively operates as the degree of specialization into the slave trade. I assume C and F are increasing and strictly convex in S.

Using the first order conditions and the implicit function theorem, we can obtain the follow partial derivatives:

$$\frac{\partial S}{\partial R} = \frac{C_{SR} + F_{SR}}{P_{SS}S + 2P_S - C_{SS} - F_{SS}} \tag{2}$$

and

$$\frac{\partial S}{\partial T} = \frac{C_{ST} + F_{ST}}{P_{SS}S + 2P_S - C_{SS} - F_{SS}}. \tag{3}$$

I let

$$P_{SS}S + 2P_S - C_{SS} - F_{SS} < 0, \tag{4}$$

which will occur as long as both the degree of convexity in the demand curve faced by the individual and the degree of specialization into the slave trade are relatively small. It was rare for an individual to hold a monopoly on any aspect of the slave trade.[12] Even if an individual happened to be a coastal ruler with a monopoly on the slave trade at a given port, he would face competition from the other slave exporting ports. The inter- and intra-port competition imply the individuals are probably price takers, which means the assumption in equation (4) is likely valid.

My empirical estimates suggest that $\frac{\partial S}{\partial R} < 0$ and $\frac{\partial S}{\partial T} < 0$. The negative estimates, along with the assumption that the denominator is negative, imply that $F_{SR} + C_{SR} > 0$ and $F_{ST} + C_{ST} > 0$. However, without further knowledge on the signs of F_{ST}, F_{SR}, C_{ST}, and C_{SR}, the primary mechanisms (explicit C or opportunity F costs) through which rainfall and temperature impact the slave trade are ambiguous.

A priori knowledge suggests positive rainfall shocks and negative temperature shocks tend to increase both farm revenues and agricultural production in Africa (Kurukulasuriya and Mendelsohn, 2008; Barrios, Ouattara and Strobl, 2008). Increased agricultural yields increase the opportunity costs of participating in the slave trade. Climate shocks also lead to income shocks. During a severe drought, the opportunity costs of not increasing participation in the slave trade may be starvation. In the absence of other methods to smooth consumption over prolonged periods, individuals may be forced to specialize to the point of self-selecting themselves, their friends, or their family members into the slave trade to prevent starvation.[13] Other forms of specialization and consumption smoothing include kidnapping (Sparks, 2014, 135-138), the sale of pawned Africans into the slave trade (Lovejoy, 2012, 13), and conflict (Lovejoy, 2012, 85).[14] Therefore, I let $F_{ST} < 0$ and $F_{SR} > 0$.

We can do a similar exercise for C. First, I let $C_{ST} > 0$, because higher temperatures increase the costs associated with the procurement of an additional slave through mechanisms such as the disease burden, agricultural costs, and heat exhaustion. The sign of C_{SR} is less clear. There are two main competing mechanisms: the disease burden, such as malaria, and agricultural-induced changes in explicit costs, such as feeding a slave raiding army. Droughts made Africans weak and more susceptible to European diseases, (Dias, 1981). On the other hand, the prevalence of cholera and malaria both increase with increased precipitation (Reyburn et al., 2011; Zhou et al., 2004). Anecdotal evidence suggests that while Africans

[12]For example, in Old Calabar, slave ships frequently bought from multiple, sometimes more than ten, slave traders in a single voyage (Behrendt, Latham and Northrup, 2010).

[13]In one sample of freed slaves in Sierra Leone, nearly 20 percent of the former slaves were tricked or sold by a friend or relative into the slave trade (Nunn, 2012).

[14]Both contemporary and historical evidence suggest a strong correlation between droughts and conflict (Calderone, Maystadt and You, 2015; Hsiang, Burke and Miguel, 2013; Miller, 1982; Lovejoy, 2012, 69).

primarily suffered from European diseases during periods of drought, Europeans primarily suffered from African diseases during periods of increased rainfall (Miller, 1982). An increase in rainfall also increases agricultural output, which lowers the explicit costs associated with the slave trade. Thus, while the African disease burden would suggest $C_{SR} > 0$, the European disease burden and agricultural costs would suggest $C_{SR} < 0$.

Since $C_{ST} > 0$ and $F_{ST} < 0$, the model suggests that temperature primarily impacts the slave trade through the explicit cost mechanism C_{ST}. On the other hand, the impact of rainfall operates through either the opportunity cost mechanism F_{SR} or the African disease burden $C_{SR} > 0$.

4.2 Opportunity Cost or Disease Burden?

The model and results suggest two possible mechanisms for the negative relationship between rainfall and slave exports — the opportunity cost of agriculture and the disease burden. I examine each in turn.

To examine whether the impact of rainfall on slave exports depends on the degree of correlation between rainfall and agricultural income, I interact the rainfall and temperature anomalies with the port's AEZ zone and dominant agricultural crop as shown in Columns (1) and (2) of Table 4.

I find that positive rainfall anomalies decrease slave exports primarily in sub-humid, humid forest, and moist savannah regions. These AEZ zones tend to produce crops that are more reliant on rainfall levels, such as cereals. Moreover, the estimates suggest that a positive rainfall shock actually increases slave exports in desert regions. These results could be due to the fact that desert regions tend to have crops that are less dependent on rainfall. Agriculture in desert regions also tends to be irrigated, which further reduces the reliance on rainfall levels.

The results on dominant crop in Column (2) tell a similar story. Negative rainfall shocks and droughts have a larger impact in areas that primarily grew roots and cereals, which are heavily dependent on rainfall, versus areas that primarily grew tree crops, which are less dependent on rainfall. Ports which are assigned no dominant crop, and thus were likely not tied to agriculture for sustenance, actually exhibit a positive relationship with slave exports.

The negative relationship between rainfall and slave exports could also be driven by the explicit cost of the African disease burden.[15] To test the potential impact of the African disease burden, I interact Rain_{t-1} and the port's average malaria suitability. The results of this can be seen in Column (3) of Table 4. The interaction between rainfall and malaria suitability is negative, but statistically insignificant at conventional levels. Furthermore, the interaction does little to reduce the magnitude or significance of the negative relationship between Rain_{t-1} and slave exports. This seems to suggest that the African disease burden is not the primary mechanism.[16]

One issue with this empirical exercise is the high degree of correlation between the measure of malaria suitability and each region's AEZ classification and dominant crop type. The correlation can be seen in Figures A7 – A9. This correlation makes it hard to separate the opportunity cost and disease burden mechanisms. However, there at least two additional reasons why one might favor an opportunity cost interpretation. First, the historical literature emphasizes the consumption smoothing role of the slave trade in response to climate shocks, and while the disease burden is mentioned, the sign for the combined impact of the European and African disease burden is ambiguous. Second, the temporally lagged

[15] One alternative hypothesis does involve the European disease burden. Specifically, if slave merchants, afraid of losing their inventory to a smallpox epidemic, sell a large proportion of their stock of slaves in response to a drought, then we could see similar results. However, this seems unlikely to be driving the entirety of the result.

[16] On the other hand, the results at the region level, displayed in Column (3) of Table B5, show a significant negative interaction between rainfall and malaria.

Table 4: Mechanisms

	Dependent Variable: Slave Exports				
	(1)		(2)		(3)
$Rain_{t-1}$ ×		$Rain_{t-1}$ ×		$Rain_{t-1}$ ×	
Desert	253.3**	Cereals	-218.3***	1	-253.6***
	(108.8)		(72.72)		(56.32)
Dry Savannah	32.84	Roots	-332.7***	Malaria	-55.13
	(68.83)		(100.0)		(68.12)
Humid Forest	-306.6***	Trees	97.86		
	(105.7)		(64.40)		
Moist Savannah	-228.7**	None	1533.5***		
	(107.0)		(273.9)		
Sub-Humid	-456.9***				
	(162.3)				
$Temp_t$ ×		$Temp_t$ ×		$Temp_t$ ×	
Desert	-1256.7	Cereals	-1812.0	1	-1004.6
	(1176.5)		(1400.3)		(1533.4)
Dry Savannah	-2368.5	Roots	42.89	Malaria	1058.8**
	(1651.0)		(2099.4)		(516.1)
Humid Forest	2357.8	Trees	1770.1*		
	(2603.9)		(946.6)		
Moist Savannah	-403.0	None	2849.2**		
	(1776.3)		(1108.4)		
Sub-Humid	-886.3				
	(1633.2)				
Port F.E.	Yes		Yes		Yes
Year F.E.	Yes		Yes		Yes
Obs.	7995		7995		7995

Notes: Tobit regressions with standard errors clustered by homogeneous rainfall region. AEZ (crop) variables are binary indicators for the dominant AEZ zone (crop type) of the closest administrative unit (ethnic group). Including an interaction between the flood indicator and the AEZ, crop, and malaria variables makes no significant changes to the interactions reported above, though the interaction between the flood indicator and malaria is positive and significant.

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

impact of rainfall on the slave trade does not suggest a disease burden interpretation. While there can be inter-annual impacts of rainfall on malaria and tuberculosis, we would still expect to see at least some contemporary impacts of rainfall on the slave trade if the African disease burden is the primary mechanism driving the negative relationship (Pascual et al., 2008; Reyburn et al., 2011). On the other hand, individuals base their initial labor allocations between agriculture and the slave trade on the expected amount of rainfall for the year, which can be proxied by Rain $Trend_t$ in Table 3. Furthermore, individuals who originally allocated their labor to agriculture may be forced to engage in various consumption smoothing activities if low rainfall levels induce a poor harvest. These individuals will likely exhaust less extreme consumption smoothing strategies before engaging themselves, their family, or their neighbors in the slave trade. So the consumption smoothing effects of a poor harvest in the previous year spill over into the contemporary year, as suggested by Rain $Shock_{t-1}$ in Table 3.

Thus, consumption smoothing and shifts in labor allocation are my preferred mechanisms, though I cannot eliminate the possibility that the result is being driven by the explicit costs of the disease burden.

4.3 Case Study: Angola

The climate had various short- and long-run implications on the slave trade. Long-run climate changes altered the comparative advantage of regions and caused sustained shifts in labor specialization. Climate shocks led to consumption smoothing strategies, such as self-selecting into slavery or migrating. Temporary shifts in specialization were another way to smooth consumption during climate shocks. Angola is an ideal case study because it exhibited all of these coping mechanisms and produced more than a third of the total slave exports between 1801 and 1866.

4.3.1 Imbangala

The Imbangala are an example of a group that altered the allocation of their labor in response to long-run changes in climate conditions. The Imbangala were a band of raiders that emerged in the late 16th century in the Angolan region of West-Central Africa. Their emergence corresponds with a prolonged period of drought in the region. While the timing of the emergence of the Imbangala could be considered a coincidence, Miller (1982) traces the intricate relationship between the Imbangala and the drought. Beyond the timing of the Imbangala's presence, their cultural practices also reflect drought-induced desperation. These practices include cannibalism, felling stands of palm trees, and a perverse mockery of the traditional ceremonies associated with the local rain kings. Their descendants were also one of the few cultural groups to preserve an oral history of the drought. While most African societies were based upon kinship, the Imbangala operated as a 'warrior fraternity' which accepted new members through initiation ceremonies (Miller, 1976, 232-3). This allowed desperate individuals to join the warrior band in an attempt to avoid drought-induced famines. The ability to add an unlimited number of recruits to their ranks was a large contributing factor to the success of the Imbangala (Miller, 1976, 237).

The Imbangala plundered and terrorized the more sedentary populations in the area, and the slave trade increased the profitability of these activities. The Imbangala also allied themselves with the Portuguese and participated in a string of successful attacks against local African rulers, which no doubt included captured slaves as a part of the spoils. However, when the drought ended and the rains returned, groups of the Imbangala began to integrate back into the more sedentary population and returned to their agricultural roots. Oral stories from their descendants note the return of the rain as a reason for this resettlement (Miller, 1982).

4.3.2 Benguela

Benguela is located on the coast of present-day Angola and was one of the most important ports during the trans-Atlantic slave trade. Initially invaded by the Portuguese in 1617, Benguela was under Portuguese control until 1975. During this time, it is estimated that Benguela exported more than 700,000 slaves (Candido, 2013, 3-5). Like most ports, Benguela participated in the slave trade long before the arrival of Europeans. However, the Portuguese elevated the institution of slavery and entrenched it within the local economy. Being a Portuguese colony during the height of the slave trade, Portuguese officials and the Portuguese army actively participated in the slave trade and in raids along the coast (Candido, 2013, 9-17).

Slave ports bustled with economic activity and were not limited to trading slaves, but often had thriving side markets in ivory, palm oil, and agricultural goods. European demand caused the allocation of resources to shift in the surrounding region from producing nutritional crops to producing cash crops, such as palm oil, peanuts, and coffee (Dias, 1981). The shift in agricultural allocation further decreased the availability and increased the price of food in the region during droughts, which had stark impacts on the ability of the poor to procure enough food for their households. On the other hand, the frequent arrival of ships meant that slave ports were able to receive shipments of grain and food from other regions during droughts. Thus, slave ports became the home to numerous transient migrants during periods of low rainfall.

Between 1837 and 1841, the region surrounding Benguela suffered a severe drought. This led to an influx of migrants seeking refuge and food (Dias, 1981). Migrants, whether fleeing raiders or fleeing droughts, often became slaves themselves and took up positions of servitude in order to survive economic hardships (Behrendt, Latham and Northrup, 2010, 110). This can be thought of as an extreme form of consumption smoothing as individuals exchanged their freedom in return for a guaranteed level of consumption. Miller (1982) notes that the practice of refugees becoming slaves in return for sustenance was common across African ports and re-invigorated the slave trade in these locales. In addition to exchanging their freedom for food, migrants were also vulnerable to kidnappings and other forms of violence. Leaving one's home meant leaving the social ties that helped provide protection against kidnappings. The use of kidnapping was particularly prominent along the Angolan coast and the increased availability of unprotected migrants would have allowed the practice to flourish during droughts (Candido, 2013, 18).

4.3.3 More Angolan Droughts

Other locations along the Angolan coast exhibited similar responses to periods of low rainfall. In 1857, after a two-year drought in Kisama, migrants flooded the markets in Kwanza exchanging themselves and their children for grain. Locals from the surrounding area flocked to the markets to take advantage of the surplus of slaves, many of them children sold by their relatives, at substantially reduced prices (Dias, 1981). Despite occurring during the waning moments of the Atlantic slave trade, many of these refuges found themselves on European slave ships headed for the Caribbean.

A similar event occurred in the Novo Redondo portion of Angola in the late 1870s (Dias, 1981). Again, desperate households resorted to selling themselves or their relatives into slavery in an effort to survive. The magnitude of desperation resulted in a shipment of 512 people to São Tomé by the Banco Natacional Ultramarino's recruiters in October 1877, when typical shipments were half this size. Similar events are recorded to have happened in response to climate shocks as late as the 1920s in the Dande and Zaire river regions (Dias, 1981).

Furthermore, in Angola and the surrounding regions, the population's faith in its ruler partially depended on the ruler's supposed ability to control the rains. Periods of drought led to increased conflict along the African coast, as military campaigns were mounted by kings and chiefs trying to preserve their kingdom and image (Miller, 1982). The increase in conflict would then lead to a subsequent rise in slave exports.

5 Conclusion

This paper is the first attempt to empirically examine the relationship between rainfall levels and the slave trade. I have shown that negative rainfall shocks and droughts increased the number of slaves exported from the corresponding region, which confirms the hypothesis proposed by historians of the African slave trade (Miller, 1982; Dias, 1981; Newitt, 1995; Lovejoy, 2012). As households receive negative income shocks associated with droughts, they are more likely to engage in extreme consumption smoothing strategies, such as selling a member of the household into slavery. Long-run climate trends can also shift labor allocation towards slave acquisition activities. Brooks (2003, 102-3) suggests that the period from 1630 to 1820 was drier than other periods in Africa's history. If this is a valid claim, my results imply that a non-trivial amount of the total number of slaves exported from Africa can be attributed to climate conditions in Africa.

One limitation of this study is the inability to distinguish with certainty the mechanisms through which rainfall impacts slave exports. The disease burden and the opportunity cost mechanisms would both give similar results. While the historical anecdotes and temporal lag corroborate the latter mechanism, I can not rule out the possibility of the disease burden being the primary mechanism. This study also does not examine the impact of rainfall fluctuations on the internal African slave trade. Not every African slave was exported. Instead, slaves were often used as farm laborers, soldiers, and household servants within the continent. However, it is unlikely that the consumption smoothing behavior would be different.

These results also have contemporary policy implications. First, if consumption smoothing motivated participation in the African slave trade, then contemporary policy measures targeted towards assisting households smooth consumption, such as insurance and other financial products, may reduce the likelihood of households resorting to more extreme consumption smoothing choices, such as human trafficking. This is an unexplored area from both the cost-benefit analysis of microfinance and the determinants of contemporary human trafficking. As more data at the micro-level becomes available, researchers should continue to examine this relationship. Second, these results confirm the significance of historical events on development outcomes. While modern policy can be effective, it is important to recognize the historical determinants of development (Nunn, 2009). Furthermore, policymakers today should recognize that climate anomalies and climate change can have a significant and persistent impact on development when interacting with historical events.

References

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham. 2015. "Booms, Busts, and Household Enterprise: Evidence from Coffee Farmers in Tanzania." *Working Paper.*

Alonso, David, Menno J. Bouma, and Mercedes Pascual. 2011. "Epidemic Malaria and Warmer Temperatures in Recent Decades in an East African Highland." *Proceedings of the Royal Society B*, 278(1712): 1661–1669.

Barrios, Salvador, Bazoumana Ouattara, and Eric Strobl. 2008. "The Impact of Climatic Change on Agricultural Production: Is it Different for Africa?" *Food Policy*, 33(4): 287–298.

Behrendt, Stephen, A.J.H. Latham, and David Northrup. 2010. *The Diary of Antera Duke, an Eighteenth-Century African Slave Trader.* Oxford University Press.

Brooks, George E. 2003. *Eurafricans in Western Africa: Commerce, Social Status, Gender, and Religious Observance from the Sixteenth to the Eighteenth Century.* James Currey.

Calderone, Margherita, Jean-Francois Maystadt, and Liangzhi You. 2015. "Local Warming and Violent Conflict in North and South Sudan." *Journal of Economic Geography*, 15(3): 649–171.

Candido, Mariana P. 2013. *An African Slaving Port in the Atlantic World: Benguela and its Hinterland.* New York:Cambridge University Press.

Cho, Seo-Young. 2015. "Human Trafficking, A Shadow of Migration: Evidence from Germany." *Journal of Development Studies*, 51(7): 905–921.

Cho, Seo-Young, Axel Dreher, and Eric Neumayer. 2013. "Does Legalized Prostitution Increase Human Trafficking?" *World Development*, 41: 67–82.

Corno, Lucia, and Alessandra Voena. 2015. "Selling Daughters: Age at Marriage, Income Shocks and Bride Price Tradition." *Working Paper.*

Crost, Benjamin, Claire Duquennois, Joseph H. Felter, and Daniel I. Rees. 2015. "Climate Change, Agricultural Production and Civil Conflict: Evidence from the Phillipines." *Working Paper.*

Curtin, Philip D. 1975. *Economic Change in Precolonial Africa: Senegambia in the Era of the Slave Trade.* University of Wisconsin Press.

Dalton, John T., and Tin Cheuk Leung. 2014. "Why is Polygyny More Prevalent in Western Africa?: An African Slave Trade Perspective." *Economic Development and Cultural Change*, 62(4): 599–632.

Dalton, John T., and Tin Cheuk Leung. 2015*a*. "Being Bad by Being Good: Captains, Managerial Ability, and the Slave Trade." *Working Paper.*

Dalton, John T., and Tin Cheuk Leung. 2015*b*. "Dispersion and Distortions in the Trans-Atlantic Slave Trade." *Journal of International Economics*, 96(2): 412–425.

Dias, Jill R. 1981. "Famine and Disease in the History of Angola c. 1830-1930." *The Journal of African History*, 22(3): 349–378.

Djajić, Slobodan, and Alexandra Vinogradova. 2013. "Undocumented Migrants in Debt." *Labour Economics*, 21: 15–24.

Eltis, David, Stephen Behrendt, David Richardson, and Herbert Klein. 1999. "The Trans-Atlantic Slave Trade: A Database on CD-ROM."

Fenske, James, and Namrata Kala. 2015. "Climate and the Slave Trade." *Journal of Development Economics*, 112: 19–32.

Gething, Peter W., Thomas P. Van Boeckel, David L. Smith, Carlos A. Guerra, Anand P. Patil, Robert W. Snow, and Simon I. Hay. 2011. "Modelling the Global Constraints of Temperature on Transmission of Plasmodium Falciparum and P. Vivax." *Parasites & Vectors*, 4(1): 92.

Greene, William. 2002. "The Bias of the Fixed Effects Estimator in Nonlinear Models." *Working Paper.*

Henderson, J. Vernon, Adam Storeygard, and David N. Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review*, 102(2): 994–1028.

Hoogeveen, Johannes, Bas Van Der Klaauw, and Gijsbert Van Lomwel. 2011. "On the Timing of Marriage, Cattle, and Shocks." *Economic Development and Cultural Change*, 60(1): 121–154.

Hsiang, Solomon M., Marshall Burke, and Edward Miguel. 2013. "Quantifying the Influence of Climate on Human Conflict." *Science*, 341.

Jappelli, Tullio, and Luigi Pistaferri. 2010. "The Consumption Response to Income Changes." *Annual Review of Economics*, 2(1): 479–506.

Joarder, Mohammad Abdul Munim, and Paul W. Miller. 2013. "A Theoretical Perspective on Human Trafficking and Migration-Debt Contracts." *Journal of Development Studies*, 49(10): 1332–1343.

Kala, Namrata, Pradeep Kurukulasuriya, and Robert Mendelsohn. 2012. "The Impact of Climate Change on Agro-ecological Zones: Evidence from Africa." *Environment and Development Economics*, 17(6): 663–687.

Kurukulasuriya, Pradeep, and Robert Mendelsohn. 2008. "A Ricardian Analysis of the Impact of Climate Change on African Cropland." *African Journal of Agricultural and Resource Economics*, 2(1).

Lovejoy, Paul E. 2012. *Transformations in Slavery: A History of Slavery in Africa.* New York:Cambridge University Press.

Lovejoy, Paul E., and David Richardson. 1995. "British Abolition and its Impact on Slave Prices Along the Atlantic Coast of Africa, 1783-1850." *Journal of Economic History*, 55(1): 98–119.

Mahmoud, Toman Omar, and Christoph Trebesch. 2010. "The Economics of Human Trafficking and Labour Migration: Micro-evidence from Eastern Europe." *Journal of Comparative Economics*, 38(2): 173–188.

Mann, Michael E., Raymond S. Bradley, and Malcolm K. Hughes. 1998. "Global-Scale Temperature Patterns and Climate Forcing over the Past Six Centuries." *Nature*, 392(6995): 779–787.

Miller, Joseph C. 1976. *Kings and Kinsmen: Early Mbundu States in Angola.* Oxford University Press.

Miller, Joseph C. 1982. "The Significance of Drought, Disease and Famine in the Agriculturally Marginal Zones of West-Central Africa." *Journal of African History*, 23(1): 17–61.

Morduch, Jonathan. 1995. "Income Smoothing and Consumption Smoothing." *Journal of Economic Perspectives*, 9(3): 103–114.

Murdock, George P. 1967. "Ethnographic Atlas: A Summary." *Ethnology*, 6(2): 109–236.

Newitt, Malyn. 1995. *A History of Mozambique.* C. Hurst & Co.

Nicholson, Sharon E. 1986. "The Spatial Coherence of African Rainfall Anomalies: Interhemispheric Teleconnections." *Journal of Climate and Applied Meteorology*, 25(10): 1355–1381.

Nicholson, Sharon E. 2000. "The Nature of Rainfall Variability Over Africa on Time Scales of Decades to Millenia." *Global and Planetary Change*, 26: 137–158.

Nicholson, Sharon E., Amin K. Dezfuli, and Douglas Klotter. 2012. "A Two-Century Precipitation Dataset for the Continent of Africa." *Bulletin of the American Meteorological Society*, 93(8): 1219–1231.

Nunn, Nathan. 2008. "The Long-Term Effects of Africa's Slave Trades." *Quarterly Journal of Economics*, 123(1): 139–176.

Nunn, Nathan. 2009. "The Importance of History for Economic Development." *Annual Review of Economics*, 1: 65–92.

Nunn, Nathan. 2012. "74th IAES Conference Keynote Address."

Nunn, Nathan, and Diego Puga. 2012. "Ruggedness: The Blessing of Bad Geography in Africa." *Review of Economics and Statistics*, 94(1): 20–36.

Nunn, Nathan, and Leonard Wantchekon. 2011. "The Slave Trade and the Origins of Mistrust in Africa." *American Economic Review*, 101(7): 3221–3252.

Obikili, Nonso. 2015. "The Impact of the Slave Trade on Literacy in West Africa: Evidence from the Colonial Era." *Journal of African Economies*, 25(1): 1–55.

Pascual, M., B. Cazelles, M. J. Bouma, L. F. Chaves, and K. Koelle. 2008. "Shifting Patterns: Malaria Dynamics and Rainfall Variability in an African Highland." *Proceedings of the Royal Society B*, 275(1631): 123–132.

Patterson, Orlando. 2012. "Trafficking, Gender & Slavery: Past and Present." In *The Legal Understanding of Slavery: From the Historical to the Contemporary.* Oxford University Press.

Reyburn, Rita, Deok Ryun Kim, Michael Emch, Ahmed Khatib, Lorenz Von Seidlein, and Mohammad Ali. 2011. "Climate Variability and the Outbreaks of Cholera in Zanzibar, East Africa: A Time Series Analysis." *American Journal of Tropical Medicine and Hygiene*, 84(6): 862–869.

Rosenzweig, Mark R., and Oded Stark. 1989. "Consumption Smoothing, Migration, and Marriage: Evidence from Rural India." *Journal of Political Economy*, 97(4): 905.

Sekhri, Sheetal, and Adam Storeygard. 2014. "Dowry Deaths: Response to Weather Variability in India." *Journal of Development Economics*, 111: 212–223.

Sparks, Randy. 2014. *Where the Negroes are Masters: An African Port in the Era of the Slave Trade.* Harvard University Press.

Tamura, Yuji. 2010. "Migrant Smuggling." *Journal of Public Economics*, 94(7-8): 540–548.

Whatley, Warren. 2014. "The Gun-Slave Cycle in the 18th Century British Slave Trade." *Working Paper.*

Whatley, Warren, and Rob Gillezeau. 2011. "The Impact of the Transatlantic Slave Trade on Ethnic Stratification in Africa." *American Economic Review: Papers and Proceedings*, 101(3): 571–576.

Wooldridge, Jeffrey M. 2002. *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA:MIT Press.

Zeleza, Paul Tiyambe. 1997. *A Modern Economic History of Africa.* East African Educational Publishers.

Zhou, Guofa, Noboru Minakawa, Andrew K. Githeko, and Guiyun Yan. 2004. "Association Between Climate Variability and Malaria Epidemics in the East African Highlands." *Proceedings of the National Academy of Sciences of the United States of America*, 101(8): 2375–2380.

6 Appendix: A

Table A1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Slaves Exported	410.2	1947.4	0	34927.3
Rainfall	0	1.587	-3.288	4.364
Flood	0.020	0.141	0	1
Temperature	0	0.128	-0.713	0.676
Cereals	0.553	0.497	0	1
Roots	0.390	0.488	0	1
Trees	0.049	0.215	0	1
No Dominant Crop	0.008	0.090	0	1
Desert	0.016	0.126	0	1
Dry Savannah	0.154	0.361	0	1
Moist Savannah	0.122	0.327	0	1
Humid Forest	0.407	0.491	0	1
Sub-humid	0.301	0.459	0	1
Malaria Suitability	0	1	-2.820	2.278
Rain Trend (5 year)	0.042	0.815	-2.688	2.764
Temp Trend (5 year)	0.002	0.077	-0.325	0.350
Rain Shock (5 year)	-0.025	1.715	-5.000	4.600
Temp Shock (5 year)	-0.005	0.129	-0.833	0.667
Rain Trend (10 year)	0.031	0.623	-2.148	1.924
Temp Trend (10 year)	0.001	0.063	-0.279	0.291
Rain Shock (10 year)	0.017	1.607	-4.500	4.600
Temp Shock (10 year)	-0.005	0.138	-0.785	0.543
Rain Trend (20 year)	0.032	0.405	-1.498	1.312
Temp Trend (20 year)	-0.001	0.040	-0.143	0.132
Rain Shock (20 year)	-0.018	1.628	-4.600	4.650
Temp Shock (20 year)	0.012	0.136	-0.677	0.616

Table A2: Robustness Tests

	1801 - 1810:	*1811 - 1820:*	*1821 - 1830:*	*1831 - 1840:*	*1841 - 1850:*
Rain$_{t-1}$	80.90	-201.1	-334.9	-203.1	-123.3
	(187.5)	(184.9)	(208.2)	(186.2)	(213.0)
Flood$_{t-1}$	815.2	1042.1	2063.8**	393.4	1191.0
	(859.7)	(1186.8)	(808.3)	(1642.5)	(1514.5)
Temp$_t$	53.84	-149.5	800.2	-8315.5**	-7511.5***
	(2207.7)	(1311.8)	(706.5)	(4001.1)	(1810.5)
	1851 - 1860:	*1861 - 1866:*	*West:*	*West-Central:*	*East:*
Rain$_{t-1}$	-8.018	-2982.3***	-116.2	-616.2***	995.2***
	(571.3)	(354.3)	(79.60)	(166.4)	(130.7)
Flood$_{t-1}$	-199941.4	—	484.1	1953.8**	-6266.8***
	(—)	(—)	(402.1)	(803.1)	(489.9)
Temp$_t$	11955.5	-53145.6***	-675.5	-3565.5	-3729.9
	(7849.1)	(10000.2)	(1091.3)	(3302.5)	(3992.9)
	Linear Trend:[1]	*Quadratic Trend:*[1]	*Quadratic + Year FE:*[1]	*Wooldridge (2002, 542):*[2]	*Region Aggregated:*[3]
Rain$_{t-1}$	-94.52*	-94.03*	-212.6***	-288.1***	-270.5
	(48.97)	(49.30)	(46.43)	(91.97)	(192.7)
Flood$_{t-1}$	415.6	681.4	307.3	1643.4	499.7
	(312.3)	(451.8)	(345.2)	(1230.4)	(1141.6)
Temp$_t$	-2096.7	-2676.9	-3680.8**	-993.8	-3358.0
	(1746.4)	(1920.3)	(1368.7)	(1298.1)	(2765.7)
	Normalized:[4]	*High Exports:*[5]	*Low Exports:*[6]	*No Flood Dummy:*	*Log(1 + Slaves$_{it}$):*[7]
Rain$_{t-1}$	-437.1***	-251.9***	-166.9***	-231.6***	-.045**
	(129.3)	(67.85)	(51.18)	(66.16)	(.016)
Flood$_{t-1}$	1151.5*	258.1	929.4**	—	.186
	(630.8)	(782.9)	(366.6)	(—)	(.184)
Temp$_t$	49.85	-1034.6	-787.1	-1481.5	.062
	(194.3)	(1625.6)	(658.8)	(1523.3)	(.235)
	OLS FE:[8]	*Logit FE:*[9]	*OLS First Diff:*[10]	*Bootstrap SE (Port):*[11]	*Bootstrap SE (Region):*[11]
Rain$_{t-1}$	-185.0***	-.117***	-132.1**	-280.3***	-270.5
	(39.01)	(0.039)	(47.03)	(60.40)	(201.8)
Flood$_{t-1}$	223.1	.614*	833.3*	1158.8*	499.7
	(346.6)	(.323)	(402.5)	(601.1)	(1459.1)
Temp$_t$	-1773.9	-.193	-1247.9***	-1394.6	-3358.0
	(1519.0)	(.473)	(379.4)	(1131.9)	(2569.2)

Notes: Unless otherwise specified, all specifications are Tobit regressions with port and year fixed effects. Standard errors are clustered by region in parentheses, and the dependent variable is the number of slave exports from a port in a given year.

[1] OLS with year fixed effects replaced by either port-specific linear trends, port-specific quadratic trends, or port-specific quadratic trends with year fixed effects. Sample restricted to port-years such that $\text{Slaves}_{it} > 0$.

[2] Replaces the port fixed effects with the port-specific average temperature (not anomaly) and average rainfall level.

[3] Tobit regression with robust standard errors. Data aggregated at the homogeneous rainfall region level.

[4] The rainfall and temperature variables for a given port are each normalized to have a standard deviation of one within that port.

[5] Excludes ports which average less than 22,000 slaves during the time period (or roughly 330 per year).

[6] Excludes ports which export more than 100,000 slaves during the time period (or roughly 1515 per year).

[7] OLS with the dependent variable being $Log(1 + \text{Slaves}_{it})$. Standard errors clustered by rainfall region.

[8] OLS two-way fixed effects regression with sample restricted to port-years such that $\text{Slaves}_{it} > 0$. Standard errors clustered by rainfall region.

[9] Logit regression with conditional fixed-effects. Dependent variable is an indicator for whether $\text{Slaves}_{it} > 0$. Observed information matrix used for standard errors.

[10] OLS first differences regression with year fixed effects and the sample restricted to port-years such that $\text{Slaves}_{it} > 0$. Standard errors clustered by rainfall region.

[11] Nonparametric bootstrap with 50 replicates for the main specification, whether port or region aggregated.

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

Figure A1: Slave Exports by Region

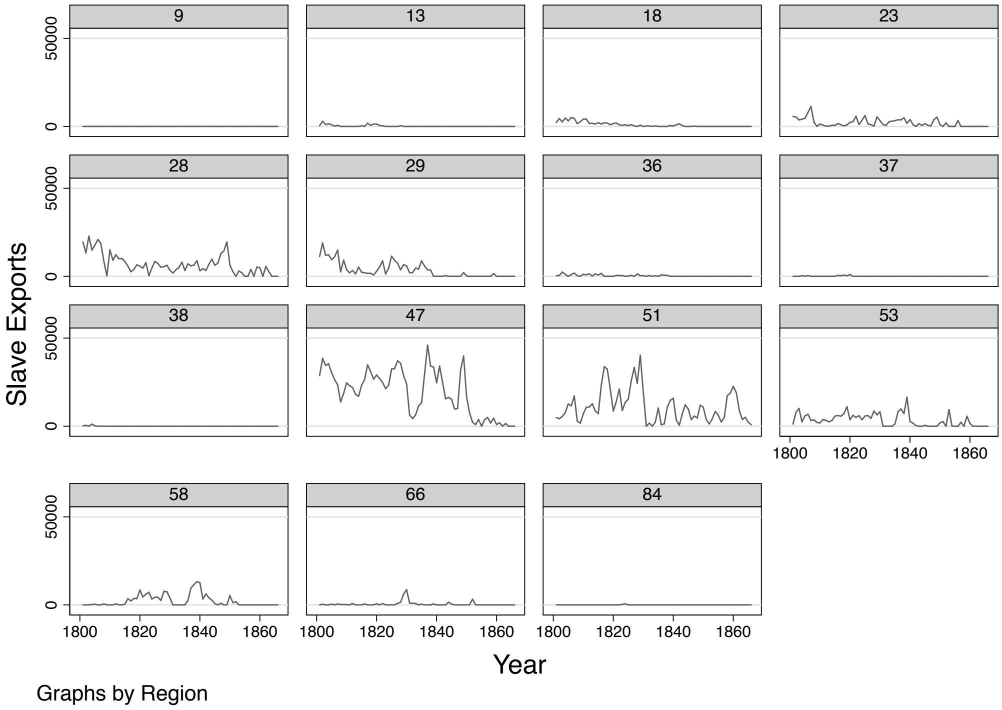


Figure A2: Rainfall Anomalies by Region

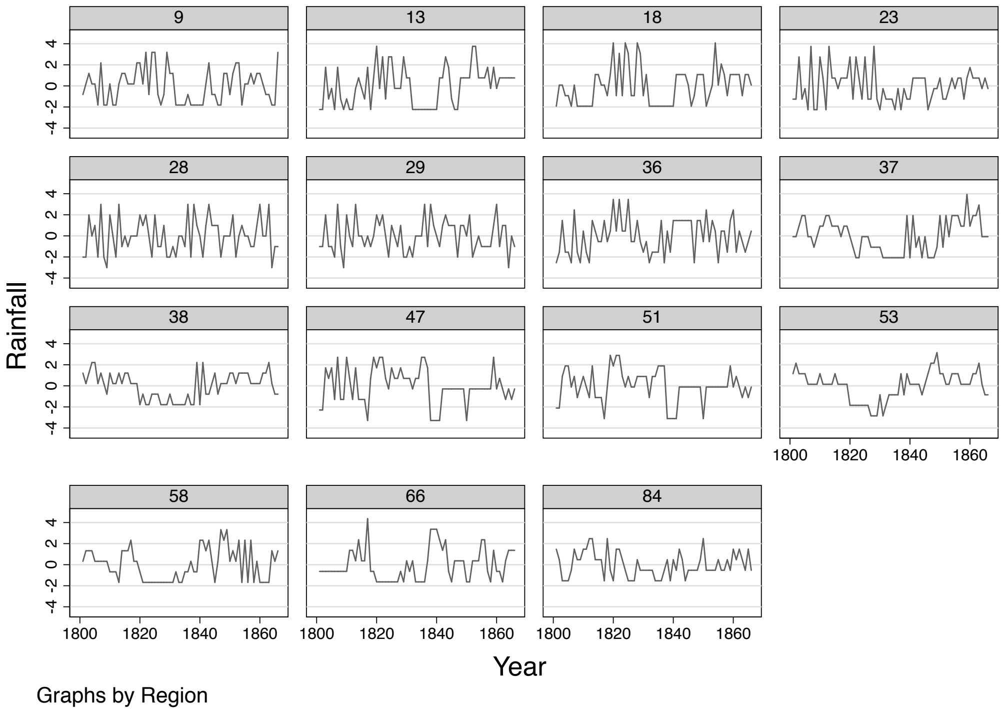


Figure A3: Temperature Anomalies by Region

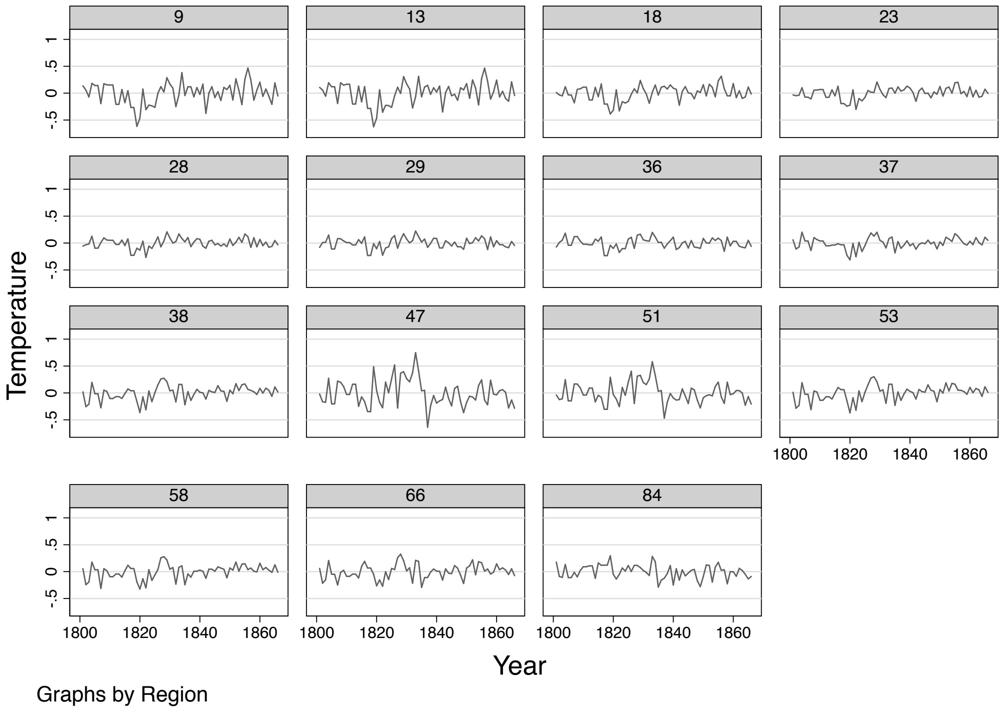


Figure A4: Total Annual Slave Exports

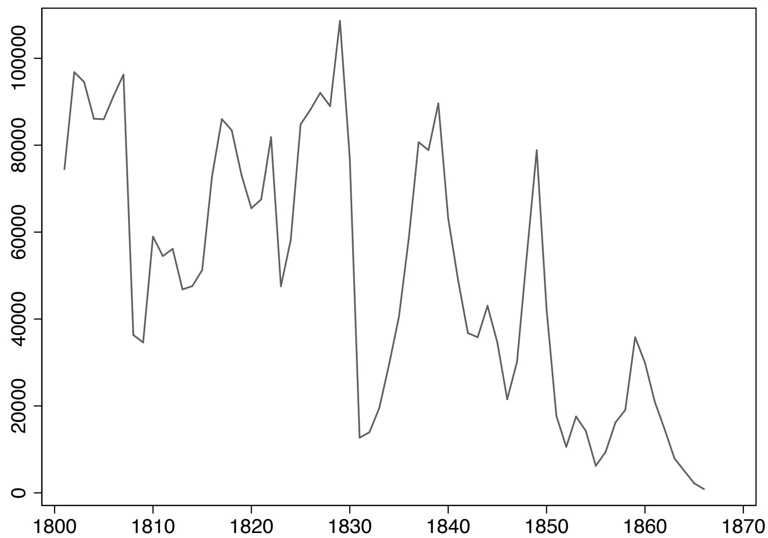


Figure A5: Total Annual Slave Exports by Regional Division

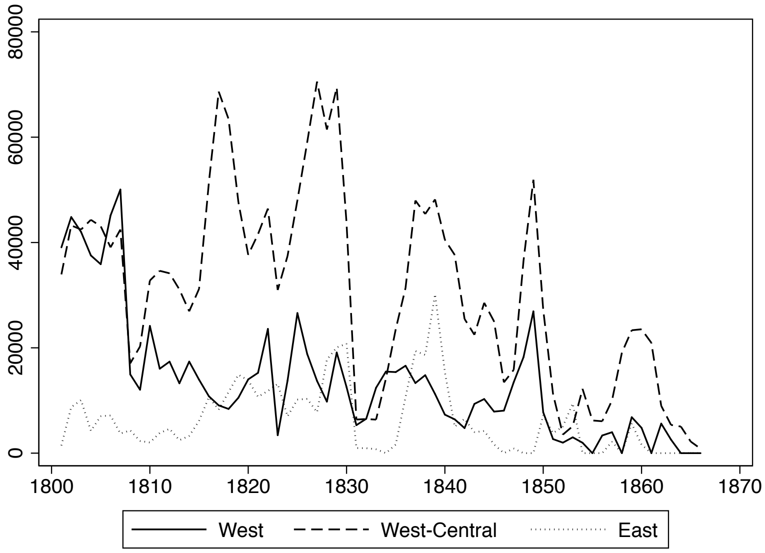
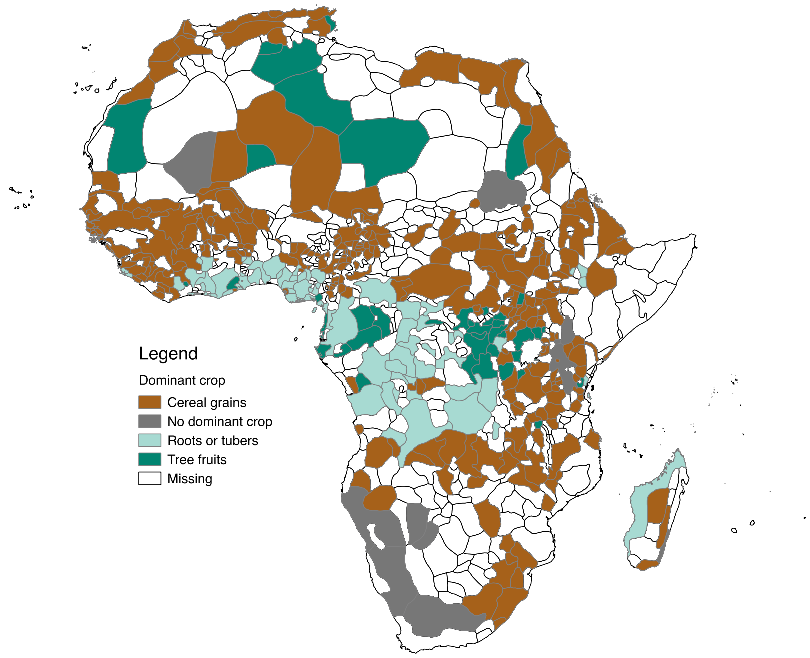


Figure A6: Temperature Points and Ports

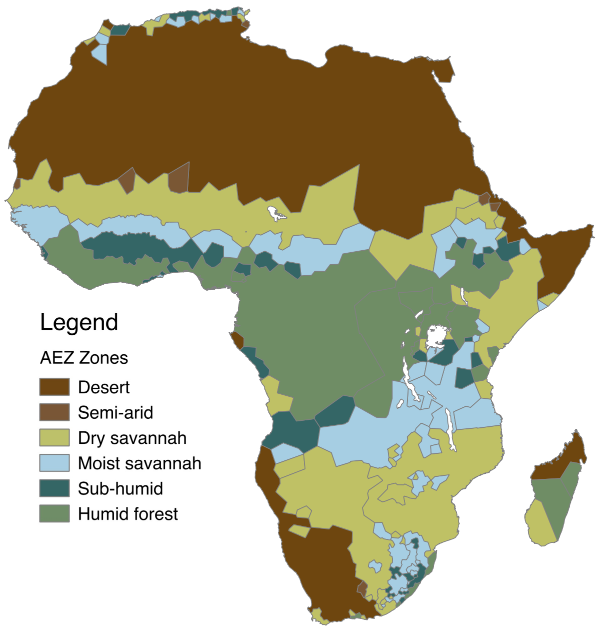
Notes: Data on temperature points comes from (Mann, Bradley and Hughes, 1998) and port locations are taken from (Fenske and Kala, 2015).

Figure A7: Dominant Crop by Ethnic Zone



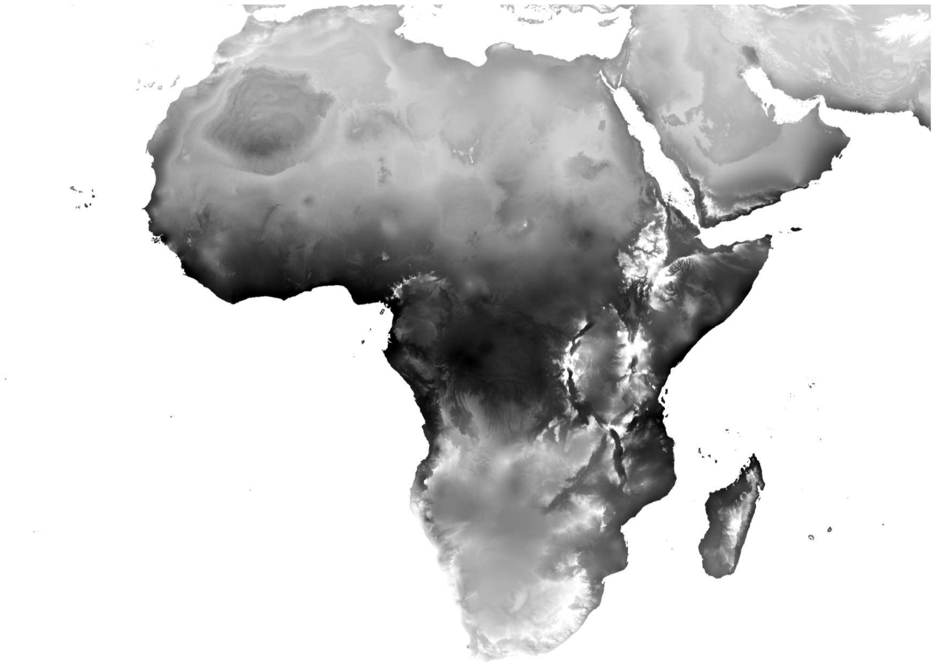
Notes: Data comes from (Murdock, 1967).

Figure A8: AEZ Zone



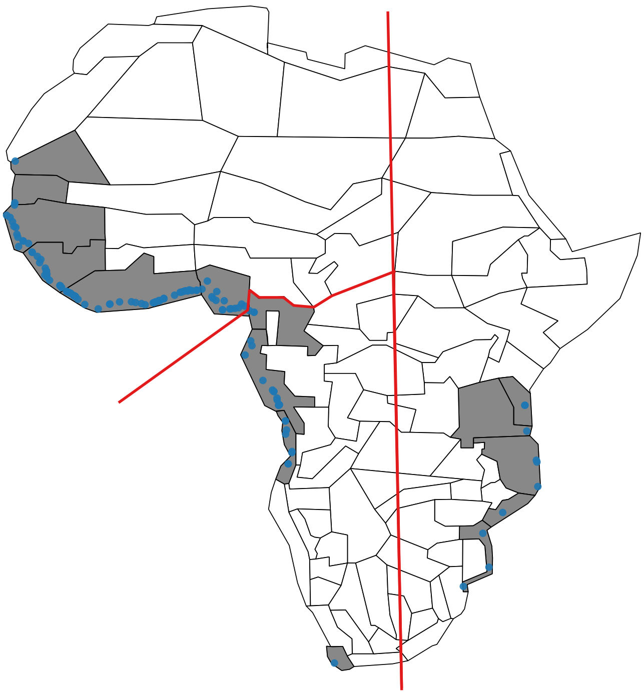
Notes: Data comes from (Kala, Kurukulasuriya and Mendelsohn, 2012).

Figure A9: Malaria Suitability



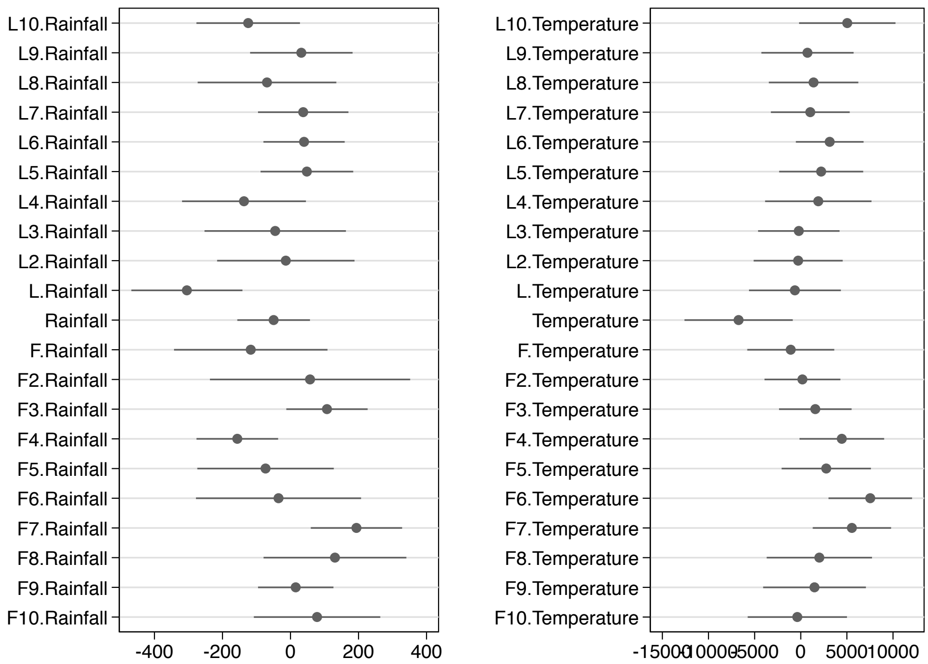
Notes: Darker regions represent areas more suitable for malaria. Data comes from (Gething et al., 2011).

Figure A10: Regional Division



Notes: Red lines marks the divisions between West, West-Central, and East Africa.

Figure A11: Lag Testing



Notes: Figure shows the coefficients along with standard errors clustered by homogeneous rainfall region from two separate regressions — one with various lagged and future values of rainfall and one with various lagged and future values of temperature. Both regressions use slave exports as their dependent variable and include year and port fixed effects. The rainfall regression also includes the flood indicator variable that corresponds to each rainfall variable. Note that 'L' denotes 'lag' and 'F' denotes 'forward'.

7 Appendix: B (Online Appendix)

7.1 Port Sample

I exclude eleven ports for being roughly greater than 75 km from the coast: Ambona, Cape Verde Islands, Fernando Po, Golf Of Guinea Islands, Madagascar, Madeira, Mascarene Islands, Mauritius (Ile De France), Princes Island, St. Lawrence, and Sao Tome. Ports not on the mainland, but within roughly 75 km of the coast are assigned the rainfall value for the region which they are closest too. Fernando Po is the closest port to the mainland that is excluded.

There are also 44 ports in the sample with no slave exports recorded after 1800: Alampo, Albreda, Andony, Apammin, Apollonia, Ardra, Arguim, Axim, Banana Islands, Boary, Cacandia, Cess, Danish Gold Coast, Dembia, Drouin, Epe, Grand Bassam, Grand Junk, Grand Popo, Iles Plantain, Joal (Or Saloum River), Lay, Legas, Little Junk, Liverpool River, Mano, Mpinda, Petit Mesurado, Portudal, Quaqua, Rio Assini, Rio Forcados, Rio Grande, River Del Rey, River Kissey, Sassandra, Scarcies, Sestos (Grand And Rock), Settra Kou, Soyo, St. Paul, Sugary, Tabou, and Wiamba.

Most of the ports with no exports after 1800 had little to no exports before this period. There are two main exceptions: Epe and Danish Gold Coast. These two ports had 76,479 and 15,949 slaves exported respectively from 1730 to 1800. Both Epe and Danish Gold Coast are in West Africa which dominated the slave trade until the slave trade shifted south after 1807. The average number of slaves exported over the entire 1730 to 1800 period for these ports, excluding Epe and Danish Gold Coast, is 1187.

7.2 Region Aggregated Results

7.2.1 Region Data Build

The rainfall variable used for each region is the rainfall level after subtracting the region-specific mean rainfall level. To assign a temperature value for each region, I create Voronoi polygons from the non-missing point data. I then rasterize the Voronoi polygons using the temperature anomalies and take the mean value for the pixels located in each homogeneous rainfall region for a given year. I then substract the region-specific mean anomaly.

The number of slaves exported from each homogeneous rainfall region is then the sum of the slaves exported from each port located within the region. This results in 15 homogeneous rainfall regions. The average region in the sample exported over 3,300 slaves annually, as shown in table B1.

A homogeneous rainfall region is assigned a value for each of the five AEZ zones based upon the proportion of the observed region (after excluding semi-arid AEZ zones) covered by the AEZ zone. For the crop variable, the entirety of each region is not covered by ethnic groups with observed values for dominant crop in the Murdock (1967) data. Therefore, a homogeneous rainfall region is assigned a value for each of the corresponding categories based upon the proportion of the *observed* region covered by ethnic zones with a dominant crop. One region has no observed values for dominant crop. This region is located at Cape Town, South Africa and is excluded from the corresponding regressions. The Cape Town region only reports slave exports during two years and has a total export level of less than 1000 slaves over both years.

The measure of malaria suitability comes from Gething et al. (2011) and can be downloaded from `http://www.map.ox.ac.uk/map/`. I use a similar rasterizing approach and then normalize the variable to have a mean of zero and a standard deviation of one.

Table B1: Summary Statistics — Region Aggregated

Variable	Mean	Std. Dev.	Min.	Max.	N
Slaves Exported	3363.3	6985.9	0	46042.2	990
Rainfall	0	1.532	-3.288	4.364	990
Flood	0.029	0.169	0	1	990
Temperature	0	0.149	-0.637	0.749	990
Cereals	0.611	0.39	0	1	924
Roots	0.222	0.303	0	0.895	924
Trees	0.135	0.249	0	0.884	924
No Dominant Crop	0.032	0.070	0	0.249	924
Desert	0.128	0.263	0	0.974	990
Dry Savannah	0.296	0.278	0	0.830	990
Moist Savannah	0.127	0.228	0	0.803	990
Humid Forest	0.228	0.306	0	0.976	990
Sub-humid	0.105	0.128	0	0.402	990
Proportion of Region Observed	0.450	0.262	0	0.809	990
Malaria Suitability	0	1	-2.594	1.172	990
Rain Trend (5 year)	0.008	0.967	-2.688	2.764	915
Temp Trend (5 year)	0.002	0.089	-0.333	0.401	915
Rain Shock (5 year)	-0.008	1.571	-5.000	4.600	915
Temp Shock (5 year)	-0.001	0.152	-0.961	0.721	915
Rain Trend (10 year)	-0.008	0.790	-2.148	1.924	840
Temp Trend (10 year)	0.002	0.071	-0.272	0.327	840
Rain Shock (10 year)	0.028	1.561	-4.500	4.600	840
Temp Shock (10 year)	-0.002	0.160	-0.895	0.565	840
Rain Trend (20 year)	-0.051	0.549	-1.498	1.312	690
Temp Trend (20 year)	-0.001	0.047	-0.130	0.147	690
Rain Shock (20 year)	0.011	1.653	-4.600	4.650	690
Temp Shock (20 year)	0.016	0.153	-0.784	0.680	690

Notes: 'Proportion of Region Observed' only applies to crop type variables. The proportion of region observed for AEZ zone is close to one.

Table B2: Non-linearity of Rainfall — Region Aggregated

Variable	Description	Slave Exports Coefficient	SE
Rain Level$_{t-1}$			
-3	Severe drought; Causes famine and/or migration	751.0	(878.3)
-2	Drought	303.6	(830.8)
-1	Dry	-76.17	(762.9)
0	Average	0	–
1	Wet	19.61	(821.8)
2	Anomalously wet	-1757.6	(1251.9)
3	Severe Rainfall; Typically causes flooding	-172.2	(1249.3)
Temp$_t$		-3887.1	(2771.9)

Notes: Tobit regression with region fixed effects, year fixed effects, and 975 observations. Dependent variable is the number of slaves exported from a region in a given year. Standard errors are robust.

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

Table B3: Trends and Shocks — Region Aggregated

	Dependent Variable: Slave Exports					
	5 Year MA		10 Year MA		20 Year MA	
	(1)	(2)	(3)	(4)	(5)	(6)
Rain Trend_t	-210.3	-214.6	-302.8	-209.7	-221.2	-80.31
	(240.9)	(237.2)	(364.6)	(365.8)	(686.3)	(768.1)
Rain Shock_{t-1}		-292.0*		-126.7		-110.3
		(162.9)		(185.4)		(246.7)
Temp Trend_t	3380.0	270.5	11180.8*	5822.4	25586.6**	17962.4*
	(4746.0)	(4568.8)	(6318.0)	(6244.9)	(11149.7)	(10893.8)
Temp Shock_t		-4519.7		-6005.1*		-5816.4
		(3153.2)		(3241.7)		(4334.7)
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	915	900	840	825	690	675

Notes: Tobit regressions with robust standard errors in parentheses. 'Rain Trend_t' is a moving average of the previous rainfall levels. 'Rain Shock_{t-1}' is the deviation from the moving average in the previous year.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table B4: Robustness Tests — Region Aggregated

	1801 - 1810:	*1811 - 1820:*	*1821 - 1830:*	*1831 - 1840:*	*1841 - 1850:*
Rain$_{t-1}$	-66.90	-557.3	-712.7**	-142.6	-532.2
	(439.0)	(376.7)	(329.9)	(388.1)	(508.3)
Flood$_{t-1}$	1932.6	1628.8	4189.1***	-3564.3	1866.0
	(2285.8)	(2386.6)	(1343.5)	(3704.6)	(2917.6)
Temp$_t$	737.4	-1889.5***	-207.4	-21419.0***	-23040.4***
	(4953.7)	(2741.7)	(4221.1)	(5247.3)	(8538.4)
	1851 - 1860:	*1861 - 1866:*	*West:*	*West-Central:*	*East:*
Rain$_{t-1}$	259.0	-4425.8***	-289.9	-1233.4**	1007.5***
	(608.0)	(1126.1)	(201.9)	(538.9)	(330.4)
Flood$_{t-1}$	76822.2	—	1090.1	1374.3	-7569.7***
	(—)	(—)	(985.7)	(3313.5)	(2248.9)
Temp$_t$	23103.9***	-55115.9**	-3439.7	-7412.2	-5406.9
	(8397.3)	(25019.3)	(2895.1)	(6335.4)	(5824.2)
	Linear Trend:[1]	*Quadratic Trend:*[1]	*Quadratic + Year FE:*[1]	*Wooldridge (2002, 542):*[2]	*Port Aggregated:*[3]
Rain$_{t-1}$	-272.9	-249.1	-280.7	-334.2	-280.3***
	(210.1)	(203.0)	(229.7)	(250.6)	(78.49)
Flood$_{t-1}$	755.2	1197.3	-781.0	3230.2**	1158.8*
	(951.7)	(939.9)	(1302.2)	(1550.0)	(640.9)
Temp$_t$	-4022.4	-5088.0*	-8167.9**	-2752.2	-1394.6
	(2941.3)	(2918.3)	(3454.6)	(3157.6)	(1509.3)
	Normalized:[4]	*High Exports:*[5]	*Low Exports:*[6]	*No Flood Dummy:*	*Log(1 + Slaves$_{it}$):*[7]
Rain$_{t-1}$	-409.7	-481.7*	-236.9*	-246.4	-.0799
	(299.6)	(257.2)	(130.4)	(164.8)	(.0643)
Flood$_{t-1}$	-448.7	1830.7	805.2	—	.664
	(1131.9)	(1986.0)	(772.0)	(—)	(.525)
Temp$_t$	97.03	-1759.2	3409.8*	-3377.7	.0519
	(359.9)	(3507.8)	(1875.2)	(2761.1)	(.690)
	OLS FE:[8]	*Logit FE:*[9]	*OLS First Diff:*[10]	*Bootstrap SE (Region):*[11]	*Bootstrap SE (Port):*[11]
Rain$_{t-1}$	-205.6	-.0546	-402.9***	-270.5	-280.3***
	(225.9)	(0.103)	(141.6)	(201.8)	(60.40)
Flood$_{t-1}$	-473.0	.938	2104.3**	499.7	1158.8*
	(1321.7)	(.811)	(962.6)	(1459.1)	(601.1)
Temp$_t$	-3659.1	-.345	-3104.8***	-3358.0	-1394.6
	(3235.9)	(1.308)	(1578.9)	(2569.2)	(1131.9)

Notes: Unless otherwise specified, all specifications are Tobit regressions with region and year fixed effects. Standard errors are robust, and the dependent variable is the number of slave exports from a region in a given year.
[1] OLS with year fixed effects replaced by either region-specific linear trends, region-specific quadratic trends, or region-specific quadratic trends with year fixed effects. Sample restricted to region-years such that $\text{Slaves}_{it} > 0$.
[2] Replaces the region fixed effects with the average rainfall level and the region-specific average temperature value after rasterizing the bilinear interpolation of the port temperature anomaly.
[3] Tobit regression with standard errors clustered by rainfall region. Data aggregated at the port level.
[4] The rainfall and temperature variables for a given region are each normalized to have a standard deviation of one within that region.
[5] Excludes regions which average less than 1,000 slave exports per year.
[6] Excludes regions which average more than 100,000 slave exports per year.
[7] OLS with the dependent variable being $Log(1 + \text{Slaves}_{it})$. Standard errors are robust.
[8] OLS two-way fixed effects regression with sample restricted to region-years such that $\text{Slaves}_{it} > 0$. Standard errors are robust.
[9] Logit regression with conditional fixed-effects. Dependent variable is an indicator for whether $\text{Slaves}_{it} > 0$. Observed information matrix used for standard errors.
[10] OLS first differences regression with year fixed effects and the sample restricted to region-years such that $\text{Slaves}_{it} > 0$. Standard errors are robust.
[11] Nonparametric bootstrap with 50 replicates for the main specification, whether port or region aggregated.
* $p < .1$, ** $p < .05$, *** $p < .01$

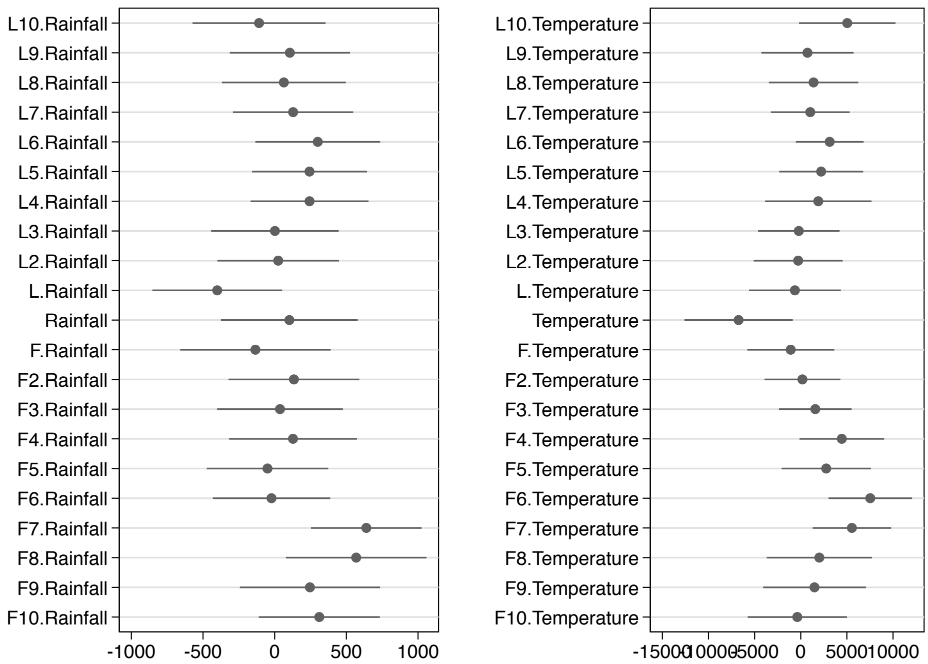
Table B5: Mechanisms — Region Aggregated

Dependent Variable: Slave Exports					
	(1)		(2)		(4)
Rain_{t-1} ×		Rain_{t-1} ×		Rain_{t-1} ×	
Desert	483.2	Cereals	-235.1	1	-116.7
	(868.1)		(179.6)		(161.1)
Dry Savannah	-11.18	Roots	-802.2*	Malaria	-404.8**
	(391.0)		(422.3)		(181.8)
Humid Forest	-687.9*	Trees	226.0		
	(415.8)		(739.6)		
Moist Savannah	-99.62	None	14154.4***		
	(598.6)		(3288.2)		
Sub-Humid	-360.7**				
	(1151.7)				
Temp_t ×		Temp_t ×		Temp_t ×	
Desert	-20147.8***	Cereals	-4011.5	1	-4139.3
	(6130.2)		(2892.7)		(2560.1)
Dry Savannah	4480.4	Roots	-6440.9	Malaria	3209.0
	(4885.8)		(6861.8)		(2264.5)
Humid Forest	19826.6**	Trees	21296.5		
	(7743.7)		(16875.9)		
Moist Savannah	-1983.7	None	-41349.9		
	(6975.6)		(26188.6)		
Sub-Humid	-25392.4**				
	(11484.1)				
Region F.E.	Yes		Yes		Yes
Year F.E.	Yes		Yes		Yes
Obs.	975		910		975

Notes: Tobit regressions with robust standard errors in parentheses. Crop and AEZ values are the proportion of the observed region covered by a given crop or AEZ type.

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

Figure B1: Lag Testing — Region Aggregated



Notes: Figure shows the coefficients along with robust standard errors from two separate regressions — one with various lagged and future values of rainfall and one with various lagged and future values of temperature. Both regressions use slave exports as their dependent variable and include year and region fixed effects. The rainfall regression also includes the flood indicator variable that corresponds to each rainfall variable. Note that 'L' denotes 'lag' and 'F' denotes 'forward'..