Title

Ancillary Costs and Benefits of Policy Shocks in a Coupled Human-Natural Environment: Insights from Schistosomiasis in Uganda

Author
Whitney, Edward M

Publication Date
2024

Peer reviewed|Thesis/dissertation

Ancillary Costs and Benefits of Policy Shocks in a Coupled Human-Natural Environment:
Insights from Schistosomiasis in Uganda

By

EDWARD MATTHEW WHITNEY

DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Agricultural and Resource Economics

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

Approved:

James N. Sanchirico, Chair

J. Edward Taylor

Michael Springborn

Committee in Charge

2024

Contents

List of Figures

List of Tables

Abstract

Despite decades of efforts by policymakers and NGOs, global prevalence of neglected tropical diseases (NTDs) persist due to the complicated relationship between the disease dynamics, human behavior, and the natural environment. In this dissertation, I investigate how targeted policy shocks can have ancillary consequences across the human-natural environment, with a focus on how such policy shocks affect local prevalence rates of Schistosomiasis (Schisto), the 2$^{\text{nd}}$ most common NTD.

I construct a novel coupled model of the human-natural environment for a small economy in the Ugandan region of Lake Victoria in Africa. I characterize the interconnectedness of the three domains of the human-natural environment—economic, public health, and biological—by defining four links between a computable general equilibrium (CGE) model of the local economy, an epidemiological model that represents the dynamics of Schisto, and a biological model that represents the growth process of the fish stock targeted by fishers in the economy. Firstly, I account for the role of public investment in disease prevention and treatment by modeling two of the epidemiological parameters as functions of aggregate income in the local economy. Secondly, I include a novel measure of exposure time to the disease, which accounts for the relationship between fishing labor and disease prevalence. Thirdly, I model the supply of effective labor as a function of disease prevalence, which accounts for the impact of infection on labor productivity. Lastly, I account for the critical relationship between fish stocks and fishing effort by modeling growth of the fish stock as a function of total harvest.

Using originally collected survey data, I develop the baseline model by estimating production function parameters, expenditure shares, and demographic characteristics for households in the local economy. Baseline household infection rates and the level of the fish stock are obtained under the assumption that the coupled model is at steady state within and between the three components. The baseline model serves as a counterfactual to the results obtained from the simulated impact of three types of policy shocks over a study period of ten years. The first policy shock is an annual exogenous increase of 1% in total factor productivity (TFP) for the oil palm sector, an important cash crop for the local economy. The TFP policy shock targets the economic domain and is representative of the types of public-private investments made in the local oil palm sector over the past twenty years. The second policy shock, a 25% reduction in fishing capital that is sustained over the 10-year study period, targets the biological domain and represents a fisheries management policy (FMP) to regulate fishing effort in order to reduce overfishing and increase future returns to fishing effort. The third policy shock targets the public health domain and is modeled as an annual decline of 19% in the mortality rate of the parasite that causes the disease. This policy shock represents community-wide programs (mass drug administration, or MDA) for treating Schisto infection, a common approach to disease management in many Schisto-affected countries.

I find that each policy shock has ancillary consequences for outcomes in the non-targeted domains. In the case of the TFP shock, large-scale, public-private partnership investments to increase cash crop yields can produce the ancillary benefit of reducing disease prevalence rates. However, they may not be sufficient for incentivizing labor reallocation away from activities correlated with disease transmission. In the case of the FMP shock, policies designed to relieve pressure on fish stocks may have the unintended consequence of increasing exposure time to the disease, thereby increasing disease prevalence rates above the counterfactual baseline. MDA programs can provide significant reductions in disease prevalence for the duration of the program, but without proper market incentives, income-generating activities associated with disease transmission may drive a resurgence in infection rates in the absence of such treatment programs. Additionally, MDA programs can offset the ancillary costs of FMP shocks for outcomes within the public health domain when implemented concurrently, while MDA-TFP concurrent shocks can produce ancillary benefits for the public health and biological domains. Additionally, labor market frictions reduce households' ability to take advantage of growth in a cash crop sector when Schistosomiasis is present.

Acknowledgements

I would like to express my deepest appreciation to my three committee members, who have been stalwart supporters and advocates for my academic career.

I am also grateful for the encouragement and support from so many people in my life, which have enabled me to persist and overcome various challenges throughout my PhD program.

I acknowledge the financial support of the Henry Jastro Research Fund.

I dedicate this dissertation to my brother, Bill.

Chapter 1

Introduction

Despite decades of efforts by policymakers, NGOs, and others, Neglected Tropical Diseases (NTDs) persist around the world (Ogongo et al., 2022; World Health Organization, 2015). The 2nd most common NTD in the world after Malaria, Schistosomiasis (shortened to Schisto below), is widely considered to be an infectious disease of poverty (World Health Organization, 2015; Centers for Disease Control, 2018). In many countries, a poor household is more likely to lack proper sanitation and access to adequate health care (Stevens, 2014), both of which have been shown to be correlated with Schisto prevalence (Grimes et al., 2014). In addition, Schisto and similar diseases can negatively impact both the accumulation process and the stock of an individual's health capital, making it even more difficult for vulnerable and poor households to avoid being trapped in a state of poverty (Bonds et al., 2010).

The worldwide persistence of Schisto may partly be a consequence of the complicated relationship between Schisto and the human-natural environment, which spans three distinct yet interconnected domains. Within the public health domain, common approaches to combating the disease include school-based and community-based distributions of drugs like Praziquantel for treatment of existing infections (King, Kittur, et al., 2020). Although additional efforts focus on changing behavioral decisions associated with water, sanitation and hygiene (WASH), poor households face constraints on their decisions related to WASH behaviors that cannot be eliminated by information campaigns alone (Torres-Vitolas et al., 2023). Additionally, some of the primary behaviors associated with transmission of the disease, such as fishing, fall squarely within the economic domain and, consequently, are likely to respond to changes in policy shocks that target economic objectives. Furthermore, the well-documented relationship between fishing effort and future fish stocks implies that fisheries management policies, which often have a focus on both the economic and biological domains, can potentially also have an impact on prevalence of Schisto.

The overarching goal of this study is to better understand how policies specific to one of the three domains within the human-natural environment can have ancillary consequences—costs or benefits—for the other domains. In pursuit of this goal, I adopt a coupled modeling approach to represent the interconnectedness of the three domains. Specifically, I link a computable general equilibrium (CGE) model of a small economy to an epidemiological model that represents the dynamics of Schisto and a biological model that represents the growth process of the fish stock targeted by fishers in the economy. The motivation for linking the public health and economic domains is informed by the well-documented relationship between economic activity and disease burden (Gallup and Sachs, 2001; Cole and Neumayer, 2006; Ismahene, 2022). The methodology that I use to connect these two domains is developed in a manner that is consistent with previous interdisciplinary efforts to study the relationship between Schisto and the human-natural environment (Bonds et al., 2010; Ngonghala, Pluciński, et al., 2014; Garchitorena et al., 2017). I adopt methods from previous bio-economic studies to link the economic domain and the biological domain, thereby allowing me to account for the critically important relationship between fishing effort and future fish stocks (Manning, Taylor, and Wilen, 2018; Gilliland, Sanchirico, and Taylor, 2019; Lindsay et al., 2020).

My dissertation contributes to the current literature in two important ways. First, by connecting a system of disease dynamics for Schistosomiasis to a CGE model of a small economy, I am able to account for differences in sectoral-level contributions to overall output, which is a novel approach that is not possible using aggregate measures of output as adopted in previous studies (e.g., Bonds et al., 2010; Ngonghala, Pluciński, et al., 2014; Garchitorena et al., 2017). This heterogeneity can be of first-order importance when the amount of labor employed in a particular sector, such as fishing, correlates with disease transmission. Furthermore, the coupled human-natural model provides a powerful tool for understanding how policies that target one domain (e.g., the local economy) can result in ancillary consequences for another domain (e.g., the ecosystem).

Second, I explicitly account for exposure time to the disease in the system of disease dynamics. This addition is critical when labor time in one sector is correlated with exposure to the disease. It is generally accepted that behavioral decisions—along with socioeconomic status, gender, and ethnicity (Moira et al., 2007)—can be factors in transmission of diseases such as Schisto (Garchitorena et al., 2017). In many communities where Schisto is prevalent, specific economic sectors such as fishing represent both an important source of income for the local economy and a core source of exposure time to the parasite that causes the disease. In these settings, including a measure of exposure time is necessary to understand whether and how policy shocks could influence welfare outcomes via disease dynamics.

To demonstrate the importance of accounting for exposure time and sector-level contributions to aggregate output, I posit a scenario wherein a change in fisheries management policy results in a relaxation of restrictions on fishing effort. Such a policy change would lead to an increase in labor demand (and thus output) in the fishing sector. Ignoring possible price effects, this policy would result in an increase in aggregate output. If one were to simulate the impact of this policy change using a model assumption that disease prevalence declines over time as aggregate income increases, the results might suggest that such a policy change would unambiguously lead to a decline in disease prevalence. However, the amount of fishing labor, and therefore exposure time to the disease, has actually increased. This increase in exposure time could dampen, or perhaps even reverse, the reduction in disease prevalence accruing from the increase in aggregate output.

My dissertation also contributes to the literature by analyzing the role of policies that target specific economic objectives can play in disease mitigation efforts. For the most part, efforts to reduce Schisto prevalence have largely focused on reducing prevalence in human hosts via the implementation of mass drug administrations (MDA) of inexpensive treatments such as Praziquantel. Integrated approaches to management of Schisto prevalence have combined MDA programs with other methods, including environmental interventions, such as molluscicides or reintroduction of natural predators of snails, improved WASH facilities, information-based interventions. Results from previous studies demonstrate the importance of a integrated approach to combating prevalence of the disease (Castonguay et al., 2020; Sun et al., 2017; Inobaya et al., 2014). However, the potential role that economic policy can play as a means to influence behavior in this context has received less attention.

In this study, I use a coupled epidemiological-biological-economic model of the human-natural environment to examine how three types of policies interact with prevalence of Schisto. Using originally collected microdata to parameterize the economic component, I model labor employed in each sector as a function of disease prevalence. In the epidemiological component, I model two parameters—the rate of human exposure to the disease and the mortality rate of the parasite in the human host—as functions of aggregate output in the local economy, and I also include an explicit measure of exposure time. To account for the relationship between fishing effort and the fish stock, I also include a dynamic model of the fish stock targeted by the local fishing industry. Using this novel coupled human-natural model, I simulate the impact of three different types of policy shocks: a policy designed to increase yields in cash-crop production by smallholder households, a fisheries management policy designed to reduce overfishing, and a community-wide distribution of treatment for Schisto.

For each type of policy, I identify the primary effects of the policy shock and any ancillary consequences of the policy for other components of the model.

1.1 Background on Schistosomiasis

Schisto is the 2nd most common NTD in the world after Malaria (World Health Organization, 2015). It is estimated that nearly 250 million people carry the parasitic worms in their body, and several hundred million more people are at risk of contracting the disease (Centers for Disease Control, 2018). The risk factors for the disease are correlated with socioeconomic status; it is for this reason that the disease is widely regarded as a disease of poverty (King, Sturrock, et al., 2006).

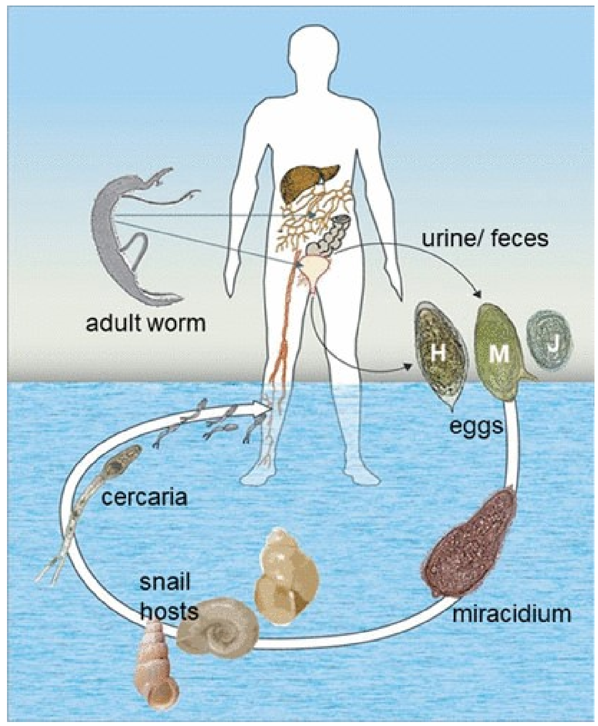


Figure 1.1: Lifecycle of the Schistosoma parasite. Adapted from Blanton (2019).

The life cycle of the Schistosoma parasite that causes the disease is depicted in figure 1.1. The Schistosoma parasite is a blood trematode, or blood fluke, that requires two hosts to complete its life cycle.[1] When the eggs produced by the adult parasite hatch, the parasite is in its immature form as miracidium and requires a freshwater snail as its intermediate host (IH). The asexual production during this phase results in cercaria, which can spend up to three days free-floating before finding a definitive host.[2]

[1]Two species of the parasite exist in the Lake Victoria environment. Schistosoma Mansoni is centered in the intestinal system and can lead to intestinal disease, liver fibrosis, and other complications, whereas Schistosoma haematobium is centered in the urinary system and can lead to inflammation and obstructive disease in the urinary system (Gray et al., 2011). This essay abstracts away from differences in the two species to focus on the effects that can occur from general symptoms that are common to both species.

[2]In this study, I focus on humans as the definitive host for the parasite. However, other mammals—

The cercaria enter the definitive host through hair follicles on the part of the body that is immersed in the water. Once inside, the cercaria make their way through blood flows to various parts of the body. The adult parasite can live an average of 3-10 years in the definitive host. During this time the worms mate and produce eggs, which are released from the human body via either urine or solid waste and can ultimately end up back in the environmental reservoir (Colley et al., 2014).

For humans, infection can only occur during direct exposure to the lake water. Such exposure can occur through a range of activities, including cleaning and other domestic chores, bathing, recreation, and fishing.[3]

The focus of this study is on fishing activity as a means of exposure. Pinot De Moira et al. (2007) document that fishing activities constitute a significant portion of total exposure time among males in their study population on Lake Victoria. In a 2013 study of a village with high prevalence rates of the disease near Lake Victoria, fishermen were more likely to have the disease and more likely to have a higher intensity of infection compared with non-fisherman (Tukahebwa et al., 2013).

The current leading approach to Schisto control is administration in group settings of the drug Praziquantel, which is known for its high efficacy, low cost, and relatively minimal side effects (Cioli et al., 2014). MDA of Praziquantel is often conducted in schools for several reasons. First, an average of eight years of mandatory school attendance across Sub-Saharan Africa means that, at least in principle, it's logistically easier and less costly to reach school-aged children than other groups (World Bank, 2022). Furthermore, it is particularly important to focus on treatment of children, given the adverse effects of infection on childhood development and lifetime earnings. In addition to school-based MDAs, community-based

including cattle, buffalo, sheep, rodents, and chimpanzees—are also vulnerable to infection (Liang et al., 2022).

[3]While it is not possible for a human to become infected by drinking water that contains parasites, infection is possible if the water touches the outer parts of the mouth, such as lips, while drinking (Centers for Disease Control, 2020).

treatments are conducted in areas of high endemicity to reach at-risk adult populations such as fishermen (Engels, 2006).

However, there are several reasons why additional strategies to control the disease beyond the MDA approach should be pursued. First, recently compiled data by UNICEF indicate that out-of-school rates for primary and lower secondary children in SSA are 20% and 30%, respectively (Unicef, 2022). Such high rates of absence make it difficult to achieve the treatment goals–75% of school aged children–provided by the World Health Organization (Engels, 2006). Second, Praziquantel is understood to be ineffective against immature worms, which means that some individuals can remain infected after treatment even if all adult worms were neutralized (Doenhoff, Cioli, and Utzinger, 2008). Third, Gurarie et al. (2018) provide evidence that disease transmission through the environment may persist despite MDAs of Praziquantel; they conclude that drug administration should be combined with other methods of combating the disease that focus on environmental transmission. Fourth, as Garchitorena et al. (2017) and others have pointed out, drug treatment may provide only a brief pause in infection for many households that have few alternatives to activities that require exposure to the disease-prevalent lake water. Perhaps more motivating, however, is the prospect of parasite resistance to drug treatment. Lab experiments (Fallon and Doenhoff, 1994) and field surveys offer mixed evidence of the potential for the parasite to develop resistance to Praziquantel, further emphasizing the need for new approaches to combat the disease (Vale et al., 2017).

Other approaches to Schisto control also face limitations in many areas impacted by the disease. Insufficient spending on water, sanitation, and hygiene (WASH) initiatives in Uganda impedes efforts to combat the disease (Loewenberg, 2014). Integrated approaches that combine drug treatment and snail control via chemical treatment of the disease-prevalent water have been successful in Egypt, China, and elsewhere (Inobaya et al., 2014). However, given potential harm for flora and fauna in the ecosystem, as well as contamination of lake water that also serves as a main water supply for local populations, chemical treatment may not be a feasible approach in the Lake Victoria setting (Hilf, 2017). Still, researchers continue to advocate innovative approaches to snail control as a vital part of the process of eliminating the disease (Sokolow et al., 2018).

Once infection occurs, Schisto can cause a variety of problems depending on the intensity of infection. Gray et al. (2011) clarify differences between acute, chronic, and advanced Schisto infection; symptoms of acute infection can include malaise, fatigue, blood in urine or feces, and acute pain. Symptoms of chronic and advanced infection include early stages of liver disease, gastrointestinal disease, and more serious complications. King, Sturrock, et al. (2006) emphasize that a high or low level of infection of the disease "contributes substantially to chronic comorbidities resulting in significant personal disability" for the infected individual (p. 576).

1.1.1 Impact of Health Status on Labor Productivity

Several studies have investigated the impact that Schisto infection can have on outcomes in the workplace. In their systematic review of previous research on productivity losses from NTDs, Lenk et al. (2016) emphasize that significant heterogeneity in infection status and intensity may contribute to the mixed evidence from population-level studies.

Audibert and Etard (2003) study households that grow rice and sorghum in Mali by employing both hired and family labor. Treatment for Schisto resulted in a 26% increase in family labor productivity on rice plots. An earlier study by Audibert and Etard (1998) found a similarly sized (23%) annualized productivity loss for family labor among rice growers in Mali. In a study of Brazilian sugarcane workers, Barbosa and Costa (1981) do not identify any impact when comparing healthy and sick workers, but they do find evidence that severe infection reduces productivity by 35% on average compared to mild infections. Kamel et al. (2002) find that infected workers worked 18% fewer hours per month and received 17.6% less in monthly incentives. The authors also found significant relationships between infection and other quality-of-life measures, such as interpersonal relationships and personal development. Finally, in an observational study of sugarcane-cutters in Tanzania, Fenwick and Figenschou (1972) identify a loss in average bonus earnings of between 3 and 5% resulting from Schisto infection.

1.1.2 Exposure Time and Infection Status Among Some Occupations

Within communities affected by the disease, exposure time and infection status can vary considerably across occupation types. Tukahebwa et al. (2013) identify an average Schistosomiasis prevalence rate of 87% among the human population in Ugandan villages on Lake Victoria; fishers had the highest levels of infection intensity among sampled individuals. Conducting an observational study on the Niger delta, Watts and Katsha (1997) find that farmers who were exposed to the disease via irrigation practices had infection rates more than double the next occupation, with infection rates for farmers in one village exceeding 50%. In a study based in China, Li et al. (2000) finds that occupational status explains nearly all of the total exposure time to the disease.

1.1.3 Prevalence of Schistosomiasis

(See Figure 1.2) 85-90% of cases of infection and a similar percentage of the global at-risk population are found in Sub-Saharan Africa (King, Sturrock, et al., 2006). Prevalence of parasitic infection in humans varies around the region, with some studies reporting prevalence rates of less than 1%, particularly in communities distant from lakes. As shown in figure 1.3, communities proximate to lakes are associated with higher prevalence rates, while communities that are far from lakes are more likely to be associated with prevalence levels below 1%, on average.

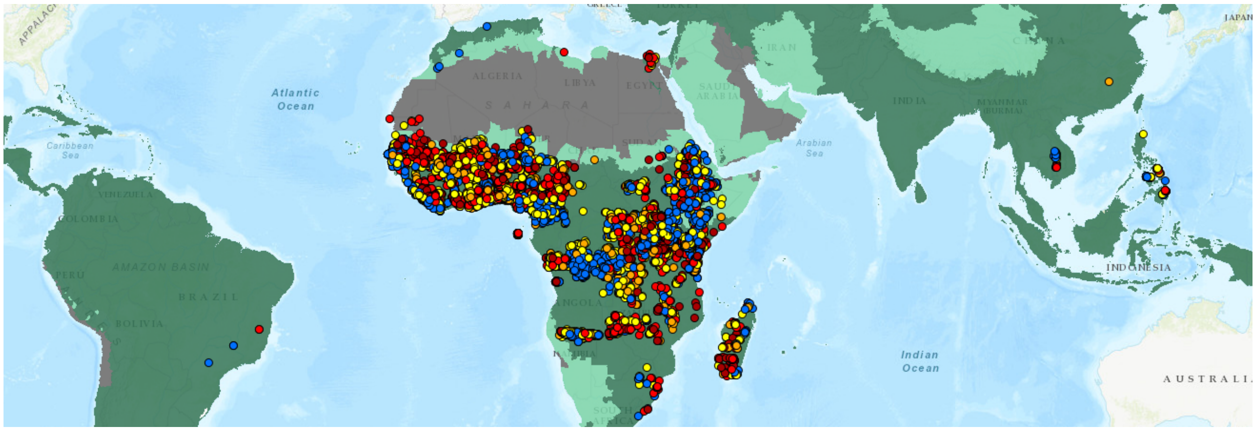


Figure 1.2: Global Schistosomiasis prevalence as measured by cross-sectional surveys since 1980. Colors are indicative of level of prevalence: blue $< 1\%$, yellow 1-10%, orange 10-20%, red 20-50%, dark red $> 50\%$. Source: Global Atlas of Helminth Infections, developed by London Applied & Spatial Epidemiology Research Group (LASER) at the London School of Hygiene and Tropical Medicine. Accessed July 12, 2023.

Lake Victoria is a known hotspot for the disease due to favorable conditions for propagation of the IH snail population (Standley et al., 2010). Eutrophication of the lake water has been associated with the widespread growth of water hyacinth across the lake (Albright, Moorhouse, and McNabb, 2004). Water hyacinth provides breeding grounds for the IH snails for the Schistosoma parasite; prevalence of water hyacinth is strongly associated with high snail population densities and transmission rates of Schisto (Desautels et al., 2022).

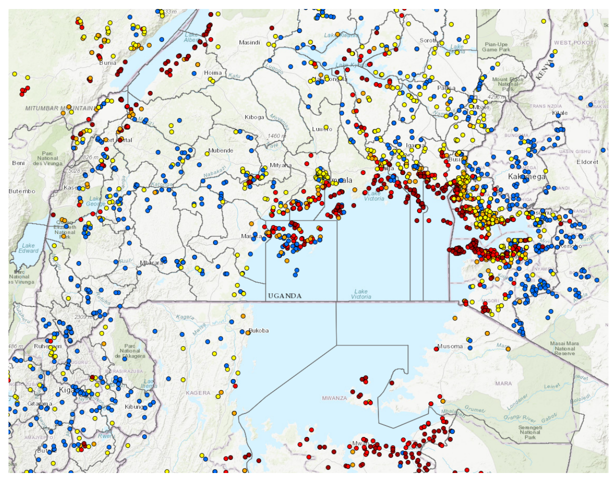


Figure 1.3: Schistosomiasis prevalence in the Lake Victoria region and surrounding areas as measured by cross-sectional surveys since 1980. Colors are indicative of level of prevalence: blue $< 1\%$, yellow 1-10%, orange 10-20%, red 20-50%, dark red $> 50\%$. Source: Global Atlas of Helminth Infections, developed by London Applied & Spatial Epidemiology Research Group (LASER) at the London School of Hygiene and Tropical Medicine. Accessed July 12, 2023.

Ssebuggwawo and Kitamirike (2005) document historical reports of water temperatures ranging between 23 and 26 degrees Celsius in the Ugandan portion of Lake Victoria. These temperatures are favorable for survival and propagation of the IH snails.

Ngarakana-Gwasira et al. (2016) report that ideal survival temperatures for survival of IH snails range between 20 and 25 degrees Celsius. Climate change may also have an impact on the prevalence of Schisto infection, with warming waters of lake environments leading to faster regeneration of IH snail populations and an increase in risk of human infection of Schisto (McCreesh and Booth, 2014).

1.2 Fishing in Lake Victoria

In the late 1950s, the Nile Perch fish was introduced into Lake Victoria in an effort to boost the productive value of the lake. The population boom of the non-native predatory Nile Perch in the 1980s brought with it an upheaval of the lake ecosystem, resulting in the permanent loss of many species (Witte et al., 1992; Downing et al., 2013). Fisheries management since then has been focused on maintaining the high-value stock of Nile Perch in the lake by regulating fishing effort. To address failures of earlier top-down approaches to fishery management, Beach Management Units were established in the mid-1990s with the goal of local ownership over management objectives; however, this strategy was not regarded as successful (Njiru et al., 2014). The 2016-2020 strategic plan of the Lake Victoria Fisheries Organization (LVFO) discusses the need to strengthen licensing of boats as a method of regulating fishing effort (Secretariat, 2016).

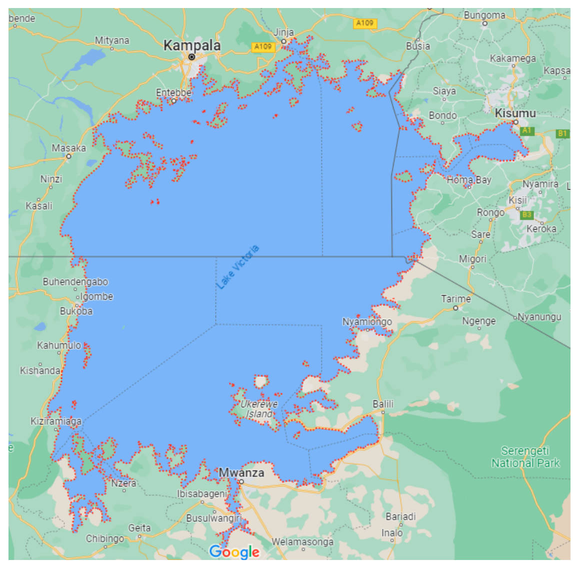


Figure 1.4: Lake Victoria and surrounding lands. Source: Google Maps, Accessed April 12, 2023.

The fisheries of Lake Victoria play a major role in the economies of Uganda, Kenya, and

Tanzania, which share its waters. Fisheries on the lake provide income for around 3 million people and revenues of over $500 million annually. Because of its critical importance to livelihoods in the region, coordinated efforts like the Lake Victoria Environmental Management Plan (LVEMP) are designed to meet the environmental challenges around the lake while also improving the welfare of the millions that depend on the lake.[4] Organizations such as the Environmental Protection Information Centre seek to contribute to this effort by aiming to "promote recovery of threatened endemic fish species and to support local communities in rebuilding their fishing villages by applying both traditional knowledge and modern science" (Ahimbisibwe, 2018).

1.3 Review of Related Methods Literature

Owing to the complex relationship between Schisto and the human-natural environment, I develop the model used in my dissertation by drawing from several different veins of literature, which I review in this section. The coupled model that I use is critical for understanding the ancillary consequences of specific types of policies in this complex study setting. For example, cash transfer programs, which have been shown to provide benefits to both recipient and ineligible households (e.g., Taylor, Filipski, et al., 2016; Gilliland, Sanchirico, and Taylor, 2019), could have the unintended consequence of increasing exposure time to the disease and thus contributing to an increase in disease prevalence. Fisheries management policies designed to improve future returns by restricting fishing effort (e.g., Manning, Taylor, and Wilen, 2018) could have the unintended effect of increasing exposure time to Schisto as a result of the increase in labor supplied to the fishing labor. Policy interactions, such as effort-restricting policy combined with investment in the agriculture sector (e.g., Lindsay et al., 2020), could also produce a non zero-sum game in which pressure on the fish stock is reduced, household incomes increase, and disease prevalence declines.

[4] The LVEMP was formed in the 2000s by the World Bank and the member states of the East African Community.

1.3.1 CGE Modeling

CGE models have been used in previous literature to study the relationship between health status and economic outcomes at the national level. Rutten and Reed (2009) develop a computable general equilibrium (CGE) model for the United Kingdom, incorporating effective labor as a measure of labor productivity while controlling for health-related demographic characteristics. Verikios et al. (2013) construct a dynamic CGE model of Australia with a more detailed representation of the labor force and the relationship between health status and labor productivity. Kabajulizi, Keogh-Brown, and Smith (2017) construct a dynamic CGE model of Uganda linked to micro-level data. In each of these studies, improvements in health status translate into welfare gains due to increased labor productivity, although the dynamics of the disease are not modeled explicitly.

I use a CGE model in this study to characterize the economic domain of the human-natural environment for a small economy. CGE models are powerful tools for capturing both direct and indirect impacts of policy interventions, particularly when experimental designs are infeasible, and can used to evaluate a range of research questions. Furthermore, CGE models allow for the appropriate focus on small-scale producer households in developing countries, for which production and labor allocation decisions are often intertwined. For example, Taylor and Filipski (2014b) employ a multi-household CGE model of the rural economy in Guatemala to reveal how global food price shocks have heterogeneous effects across smallholder and largeholder households (in terms of land), including subsistence households. Specifically, income effects from commodity price increases were offset by welfare losses for the households with less land. In a 2018 study of aquaculture in Myanmar, Filipski and Belton (2018) use a CGE model to identify increased labor demand as a key driver behind aquaculture generating higher incomes on a per-acre basis than agriculture. CGE models are also powerful tools due to their ability to capture both direct and indirect effects of policy interventions, particularly when experimental designs are infeasible. Applying a local economy-wide impact evaluation (LEWIE) model to a range of research questions, Taylor and Filipski (2014a) provide estimates of the value that a natural resource brings to a local economy, how migration flows can alter local economy impacts of policy interventions, and the impact of cash-transfer programs on non-beneficiary households.

1.3.2 Coupled Epi-Economic Models in Previous Literature

Previous studies that integrate epidemiological models with aggregate measures of economic well-being have demonstrated that poverty traps can result from the dynamics of diseases like Schistosomiasis. Bonds et al. (2010) introduce a theoretical mechanism for understanding disease-driven poverty traps, linking a susceptible-infected-susceptible model of infection dynamics to a measure of per capita aggregate income. Pluciński et al. (2013) demonstrate theoretical evidence for heterogeneous welfare outcomes across the income distribution, even with uniform initial conditions. While their model is disaggregated across representative individuals, it does not disaggregate factor inputs such as labor time across productive sectors. In their model, disease transmission is determined by per capita aggregate income, which is a function of human capital, which in turn is a function of health status. Ngonghala, Pluciński, et al. (2014) extend previous work by considering infection status as a function of multiple diseases. They model the link between infection and the economy using per capita income derived from an aggregate CES production function.

Ngonghala, De Leo, et al. (2017) contribute to this literature by considering several variations of a general coupled model that differ according to how the relationship between the economy and the resource is depicted (for instance, whether human capital plays a role, or whether the natural enemies are crop pests or human pathogens) and what values of the parameters are required to reach each of the stable equilibria. Using per capita output from an aggregate production function for the economic component, they find that a stable equilibrium in a state of poverty occurs over a large range of parameter values (approximately 55%) compared to the stable equilibrium above the poverty threshold. Garchitorena et al. (2017) provide a generalized framework for modeling the relationship between economic activity and infection status. They express several parameters in the infection dynamics as functions of per capita capital stock, which in turn transitions over time according to an aggregate production function. Their method for linking the disease dynamics to economic activity is closely aligned with the approach used in this essay.

1.3.3 Bio-Economic Models in Previous Literature

Bio-economic models integrate human decision-making with biological processes and have been used to study natural resource management across a diverse spectrum of study settings (Brown, 2000). Bioeconomic models have been applied to developing countries settings, were institutional capacity of fisheries management authorities is often constrained, and production and labor allocation decisions by fishers are interwoven with other household decisions. For example, Wilen (2013) reveal how changes in policy that result increases in future returns to fishing effort may either be pro- or anti-poor depending on initial bioeconomic conditions. Albers et al. (2021) examine how spatial policies such as marine protected areas (MPAs) interact with aspatial policies such as licensing restrictions to impact local incomes and fish stock losses. Smith et al. (2010) consider how biological or economic characteristics such as fuel costs, stock size, and outside opportunity costs may drive fishers willingness to accept short term losses such as those resulting from implementation of a marine reserve.

In the preceding studies, economic decisions are studied using partial equilibrium analysis, which means that some opportunity costs are exogenous to the model. However, for small economies in developing countries, output prices and wages may be endogenous to market outcomes. CGE models allow the researcher to account for endogenous opportunity costs can affect decisions by fishers or other actors. In related literature, researchers have employed bio-CGE models—which consist of CGE models coupled with biological population models that are used to characterize growth of fish stocks over time—in order to gain insight into the relationship between fishing effort and future fish stocks across a variety of study contexts.

For example, Gilliland, Sanchirico, and Taylor (2019) study the impact of a social cash transfer program for a local economy with a fishing sector. The CGE component of the bio-economic model sheds light on the stimulus effects of the cash transfer felt by both recipient and non-recipient households, as well as the resulting increase in demand for fishing labor, a consequence of the increased demand for fish accruing from the rise in incomes. Manning, Taylor, and Wilen (2018) use a bio-CGE model to demonstrate how misallocation of factors of production that result from open-access fisheries can lead to welfare losses within the local economy, including for households that don't participate in the fishing sector. Specifically, the authors find that a fisheries management policy that restricts fishing effort for a period of five years leads to increases in employment and wages in the fishing sector, and thus an increase in welfare for the representative consumer, in the long term.

However, as observed in Lindsay et al. (2020), policies that limit fishing effort have short-term negative consequences for household welfare, since increased enforcement in the fishery results in a decline in fishing effort and household incomes. Lindsay et al. (2020) also demonstrate how a combination of increased enforcement of current fisheries restrictions and investment in the agricultural sector can lead to reduced pressure on the fish stock while improving household incomes, a result which the researchers characterize as a "win-win" for policies focused on sustainable development objectives.

Bibliography

Ahimbisibwe, Imran (2018). *Enhancing Livelihoods of Lake Victoria Fisher Folk Through Control of the Predator Nile Perch in Uganda*. accessed 2019-5-1. URL: https://satoyama-initiative.org/wp-content/uploads/2018/05/SITR3_CS_Ahimbisibwe-web-min.pdf.

Albers, Heidi J., Madison Ashworth, Tabaré Capitán, Róger Madrigal-Ballestero, and Louis Preonas (Oct. 2021). "MPAs and Aspatial Policies in Artisanal Fisheries". In: *Marine Resource Economics* 36.4, pp. 341–367. ISSN: 2334-5985. DOI: 10.1086/715818. URL: http://dx.doi.org/10.1086/715818.

Albright, Thomas P., T. G. Moorhouse, and T. J. McNabb (July 2004). "The Rise and Fall of Water Hyacinth in Lake Victoria and the Kagera River Basin, 1989-2001". In: *Journal of Aquatic Plant Management* 42, pp. 73–84. URL: http://pubs.er.usgs.gov/publication/70026974.

Audibert, Martine and Jean-Francois Etard (1998). "Impact of Schistosomiasis on Rice Output and Farm Inputs in Mali". In: *Journal of African Economies* 7.2, pp. 185–207. URL: https://EconPapers.repec.org/RePEc:oup:jafrec:v:7:y:1998:i:2:p:185-207.

– (2003). "Productive Benefits after Investment in Health in Mali". In: *Economic Development and Cultural Change* 51.3, pp. 769–82. URL: https://EconPapers.repec.org/RePEc:ucp:ecdecc:y:2003:v:51:i:3:p:769-82.

Barbosa, F. S. and D. P. Periera da Costa (1981). "Incapacitating Effects of Schistosomiasis Mansoni on the Productivity of Sugar-cane Cutters in Northeastern Brazil". In: *American Journal of Epidemiology* 114.1, pp. 102–111. ISSN: 0002-9262. DOI: 10.1093/oxfordjournals.aje.a113156. eprint: http://oup.prod.sis.lan/aje/article-pdf/114/1/102/226727/114-1-102.pdf. URL: https://doi.org/10.1093/oxfordjournals.aje.a113156.

Blanton, Ronald E. (2019). "Population Structure and Dynamics of Helminthic Infection: Schistosomiasis". In: *Microbiology Spectrum* 7.4, p. 7.4.16. DOI: 10.1128/microbiolspec.AME-0009-2019. eprint: https://journals.asm.org/doi/pdf/10.1128/microbiolspec.AME-0009-2019. URL: https://journals.asm.org/doi/abs/10.1128/microbiolspec.AME-0009-2019.

Bonds, Matthew H., Donald C. Keenan, Pejman Rohani, and Jeffrey D. Sachs (2010). "Poverty Trap Formed by the Ecology of Infectious Diseases". In: *Proceedings of the Royal Society B: Biological Sciences* 277.1685, pp. 1185–1192. DOI: 10.1098/rspb.2009.1778. eprint: https://royalsocietypublishing.org/doi/pdf/10.1098/rspb.2009.1778.

URL: https://royalsocietypublishing.org/doi/abs/10.1098/rspb.2009.1778.
Brown, Douglas R. (2000). "A Review of Bio-economic Models". In: *Cornell African Food Security and Natural Resource Management (CAFSNRM) Program* 102.
Castonguay, François M., Susanne H. Sokolow, Giulio A. De Leo, and James N. Sanchirico (2020). "Cost-Effectiveness of Combining Drug and Environmental Treatments for Environmentally Transmitted Diseases". In: *Proceedings of the Royal Society B: Biological Sciences* 287.1933, p. 20200966. DOI: 10.1098/rspb.2020.0966.
Centers for Disease Control (2018). *CDC - Schistosomiasis*. Accessed 2019-4-11. URL: https://www.cdc.gov/parasites/schistosomiasis/index.
– (Sept. 2020). *CDC - Schistosomiasis - FAQs*. Accessed 2023-4-11. URL: https://www.cdc.gov/parasites/schistosomiasis/gen_info/faqs.html.
Cioli, Donato, Livia Pica-Mattoccia, Annalisa Basso, and Alessandra Guidi (2014). "Schistosomiasis Control: Praziquantel Forever?" In: *Molecular and Biochemical Parasitology* 195.1, pp. 23–29. ISSN: 0166-6851. DOI: https://doi.org/10.1016/j.molbiopara.2014.06.002. URL: http://www.sciencedirect.com/science/article/pii/S0166685114000759.
Cole, Matthew A. and Eric Neumayer (Aug. 2006). "The Impact of Poor Health on Total Factor Productivity". In: *The Journal of Development Studies* 42.6, pp. 918–938. DOI: 10.1080/00220380600774681. URL: https://doi.org/10.1080/00220380600774681.
Colley, Daniel G., Amaya L. Bustinduy, W. Evan Secor, and Charles H. King (June 2014). "Human Schistosomiasis". In: *Lancet* 383.9936, pp. 2253–2264. DOI: 10.1016/S0140-6736(13)61949-2. URL: https://www.ncbi.nlm.nih.gov/pubmed/24698483.
Desautels, Daniel J., Rachel B. Hartman, Maggie E. Weber, Nathan Jacob, Andrew Sun, and David J. Civitello (Dec. 2022). "Experimental Water Hyacinth Invasion and Destructive Management Increase Human Schistosome Transmission Potential". In: *Ecological Applications* 33.2. DOI: 10.1002/eap.2767. URL: https://doi.org/10.1002/eap.2767.
Doenhoff, Michael J, Donato Cioli, and Jürg Utzinger (2008). "Praziquantel: Mechanisms of Action, Resistance and New Derivatives for Schistosomiasis". In: *Current Opinion in Infectious Diseases* 21.6, pp. 659–667. DOI: 10.1097/qco.0b013e328318978f.
Downing, Andrea S., Nika Galic, Kees P. C. Goudswaard, Egbert H. van Nes, Marten Scheffer, Frans Witte, and Wolf M. Mooij (Oct. 2013). "Was Lates Late? A Null Model for the Nile Perch Boom in Lake Victoria". In: *PLOS ONE* 8.10, pp. 1–9. DOI: 10.1371/journal.pone.0076847. URL: https://doi.org/10.1371/journal.pone.0076847.
Preventive Chemotherapy in Human Helmin (2006). Tech. rep.
Fallon, Padraic G. and Michael J. Doenhoff (1994). "Drug-Resistant Schistosomiasis: Resistance to Praziquantel and Oxamniquine Induced in Schistosoma Mansoni in Mice is Drug Specific". In: *The American Journal of Tropical Medicine and Hygiene* 51.1, pp. 83–88. DOI: 10.4269/ajtmh.1994.51.83.
Fenwick, A. and B. H. Figenschou (1972). "The Effect of Schistosoma mansoni Infection of the Productivity of Cane Cutters on a Sugar Estate in Tanzania". In: *Bull World Health Organ* 47.5, pp. 567–572. ISSN: 0042-9686. URL: https://www.ncbi.nlm.nih.gov/pubmed/4540675.
Filipski, Mateusz and Ben Belton (Oct. 2018). "Give a Man a Fishpond: Modeling the Impacts of Aquaculture in the Rural Economy". In: *World Development* 110, pp. 205–223. DOI: 10.1016/j.worlddev.2018.05.023. URL: https://doi.org/10.1016/j.wo

rlddev.2018.05.023.
Gallup, J. L. and J. D. Sachs (Jan. 2001). “The Economic Burden of Malaria”. In: *Am J Trop Med Hyg* 64.1-2 Suppl, pp. 85–96.
Garchitorena, A., S. H. Sokolow, B. Roche, C. N. Ngonghala, M. Jocque, A. Lund, M. Barry, E. A. Mordecai, G. C. Daily, J. H. Jones, J. R. Andrews, E. Bendavid, S. P. Luby, A. D. LaBeaud, K. Seetah, J. F. Guégan, M. H. Bonds, and G. A. De Leo (2017). “Disease Ecology, Health and the Environment: A Framework to Account for Ecological and Socio-economic Drivers in the Control of Neglected Tropical Diseases”. In: *Philosophical Transactions of the Royal Society of London B: Biological Sciences* 372.1722. ISSN: 0962-8436. DOI: 10.1098/rstb.2016.0128. eprint: http://rstb.royalsocietypublishing.org/content/372/1722/20160128.full.pdf. URL: http://rstb.royalsocietypublishing.org/content/372/1722/20160128.
Gilliland, Ted E., James N. Sanchirico, and J. Edward Taylor (2019). “An Integrated Bioeconomic Local Economy-wide Assessment of the Environmental Impacts of Poverty Programs”. In: *Proceedings of the National Academy of Sciences* 116.14, pp. 6737–6742. DOI: 10.1073/pnas.1816093116. eprint: https://www.pnas.org/content/116/14/6737.full.pdf. URL: https://www.pnas.org/content/116/14/6737.
Gray, Darren J., Allen G. Ross, Yue-Sheng Li, McManus, and Donald P. (May 2011). “Diagnosis and Management of Schistosomiasis”. In: *BMJ* 342. 21586478[pmid], pp. d2651–d2651. ISSN: 1756-1833. DOI: 10.1136/bmj.d2651. URL: https://www.ncbi.nlm.nih.gov/pubmed/21586478.
Grimes, Jack E. T., David Croll, Wendy E. Harrison, Jürg Utzinger, Matthew C. Freeman, and Michael R. Templeton (Dec. 2014). “The Relationship between Water, Sanitation and Schistosomiasis: A Systematic Review and Meta-analysis”. In: *PLOS Neglected Tropical Diseases* 8.12, pp. 1–12. DOI: 10.1371/journal.pntd.0003296. URL: https://doi.org/10.1371/journal.pntd.0003296.
Gurarie, David, Nathan C. Lo, Martial L. Ndeffo-Mbah, David P. Durham, and Charles H. King (May 2018). “The Human-Snail Transmission Environment Shapes Long Term Schistosomiasis Control Outcomes: Implications for Improving the Accuracy of Predictive Modeling”. In: *PLOS Neglected Tropical Diseases* 12.5, pp. 1–19. DOI: 10.1371/journal.pntd.0006514. URL: https://doi.org/10.1371/journal.pntd.0006514.
Hilf, Aaron (2017). *Biology Professor Receives Funding to Fight Pervasive African Parasite.* Accessed 2019-4-12. URL: https://news.unm.edu/news/biology-professor-receives-funding-to-fight-pervasive-african-parasite.
Inobaya, M. T., R. M. Olveda, T. N. Chau, D. U. Olveda, and A. G. Ross (2014). “Prevention and Control of Schistosomiasis: A Current Perspective”. In: *Research and Reports in Tropical Medicine* 5.1722, pp. 65–75. DOI: doi.org/10.2147/RRTM.S44274.
Ismahene, Y. (2022). “Infectious Diseases, Trade, and Economic Growth: a Panel Analysis of Developed and Developing Countries”. In: *J Knowl Econ.* 13.3, pp. 2547–83.
Kabajulizi, Judith, Marcus R Keogh-Brown, and Richard D Smith (Oct. 2017). “The Welfare Implications of Public Healthcare Financing: A Macro–Micro Simulation Analysis of Uganda”. In: *Health Policy and Planning* 32.10, pp. 1437–1448. ISSN: 0268-1080. DOI: 10.1093/heapol/czx125. eprint: http://oup.prod.sis.lan/heapol/article-pdf/32/10/1437/21556892/czx125.pdf. URL: https://doi.org/10.1093/heapol/czx125.
Kamel, M.I., Y.A. Moustafa, N. Foda, S. Khashab, M. Moemen, and R.M. Abo El Naga

(2002). “Impact of Schistosomiasis on Quality of Life and Productivity of Workers”. In: *Eastern Mediterranean Health Journal* 8.2-3, pp. 354–362. URL: http://www.who.int/iris/handle/10665/119174.

King, Charles H., Nupur Kittur, Sue Binder, Carl H. Campbell, Eliézer K. N’Goran, Aboulaye Meite, Jürg Utzinger, Annette Olsen, Pascal Magnussen, Safari Kinung’hi, Alan Fenwick, Anna E. Phillips, Pedro H. Gazzinelli-Guimaraes, Neerav Dhanani, Josefo Ferro, Diana M. S. Karanja, Pauline N. M. Mwinzi, Susan P. Montgomery, Ryan E. Wiegand, William Evan Secor, Amina A. Hamidou, Amadou Garba, and Daniel G. Colley (July 2020). “Impact of Different Mass Drug Administration Strategies for Gaining and Sustaining Control of Schistosoma mansoni and Schistosoma haematobium Infection in Africa”. In: *The American Journal of Tropical Medicine and Hygiene* 103.1_Suppl, pp. 14–23. DOI: 10.4269/ajtmh.19-0829. URL: https://doi.org/10.4269/ajtmh.19-0829.

King, Charles H., Robert F. Sturrock, H. Curtis Kariuki, and Joseph Hamburger (Dec. 2006). “Transmission control for schistosomiasis – why it matters now”. In: *Trends in Parasitology* 22.12, pp. 575–582. ISSN: 1471-4922. DOI: 10.1016/j.pt.2006.09.006. URL: http://dx.doi.org/10.1016/j.pt.2006.09.006.

Lenk, Edeltraud J., William K. Redekop, Marianne Luyendijk, Adriana J. Rijnsburger, and Johan L. Severens (2016). “Productivity Loss Related to Neglected Tropical Diseases Eligible for Preventive Chemotherapy: A Systematic Literature Review”. In: *PLOS Neglected Tropical Diseases* 10.2. DOI: 10.1371/journal.pntd.0004397.

Li, Y.s, A.c Sleigh, A.g.p Ross, G.m Williams, M Tanner, and D.p Mcmanus (2000). “Epidemiology of Schistosoma japonicum in China: morbidity and strategies for control in the Dongting Lake region”. In: *International Journal for Parasitology* 30.3, pp. 273–281. DOI: 10.1016/s0020-7519(99)00201-5.

Liang, Song, Keerati Ponpetch, Yi-Biao Zhou, Jiagang Guo, Berhanu Erko, J. Russell Stothard, M. Hassan Murad, Xiao-Nong Zhou, Fadjar Satrija, Joanne P. Webster, Justin V. Remais, Jürg Utzinger, and Amadou Garba (May 2022). “Diagnosis of *Schistosoma* Infection in Non-human Animal Hosts: A Systematic Review and Meta-analysis”. In: *PLOS Neglected Tropical Diseases* 16.5. Ed. by Christine A. Petersen, e0010389. ISSN: 1935-2735. DOI: 10.1371/journal.pntd.0010389. URL: http://dx.doi.org/10.1371/journal.pntd.0010389.

Lindsay, Amanda R., James N. Sanchirico, Ted E. Gilliland, Rohani Ambo-Rappe, J. Edward Taylor, Nils C. Krueck, and Peter J. Mumby (2020). “Evaluating Sustainable Development Policies in Rural Coastal Economies”. In: *Proceedings of the National Academy of Sciences* 117.52, pp. 33170–33176. ISSN: 0027-8424. DOI: 10.1073/pnas.2017835117. URL: https://www.pnas.org/content/117/52/33170.

Loewenberg, Sam (2014). “Ugandas Struggle with Schistosomiasis”. In: *The Lancet* 383.9930, pp. 1707–1708. DOI: 10.1016/s0140-6736(14)60817-5.

Manning, Dale T., J. Edward Taylor, and James E. Wilen (Jan. 2018). “General Equilibrium Tragedy of the Commons”. In: *Environmental and Resource Economics* 69.1, pp. 75–101. ISSN: 1573-1502. DOI: 10.1007/s10640-016-0066-7. URL: https://doi.org/10.1007/s10640-016-0066-7.

McCreesh, Nicky and Mark Booth (July 2014). “The Effect of Increasing Water Temperatures on Schistosoma mansoni Transmission and Biomphalaria pfeifferi Population Dynamics: An Agent-Based Modelling Study”. In: *PLOS ONE* 9.7, pp. 1–7. DOI: 10.137

1/journal.pone.0101462. URL: https://doi.org/10.1371/journal.pone.0101462.
Moira, Angela Pinot De, Anthony J. C. Fulford, Narcis B. Kabatereine, Francis Kazibwe, John H. Ouma, David W. Dunne, and Mark Booth (2007). "Microgeographical and Tribal Variations in Water Contact and Schistosoma mansoni Exposure Within a Ugandan Fishing Community". In: *Tropical Medicine & International Health* 12.6, pp. 724–735. DOI: 10.1111/j.1365-3156.2007.01842.x.
Ngarakana-Gwasira, E.T., C.P. Bhunu, M. Masocha, and E. Mashonjowa (2016). "Transmission Dynamics of Schistosomiasis in Zimbabwe: A Mathematical and GIS Approach". In: *Communications in Nonlinear Science and Numerical Simulation* 35, pp. 137–147. ISSN: 1007-5704. DOI: https://doi.org/10.1016/j.cnsns.2015.11.005. URL: https://www.sciencedirect.com/science/article/pii/S1007570415003731.
Ngonghala, Calistus N., Giulio A. De Leo, Mercedes M. Pascual, Donald C. Keenan, Andrew P. Dobson, and Matthew H. Bonds (2017). "General Ecological Models for Human Subsistence, Health and Poverty". In: *Nature Ecology & Evolution* 1.8, pp. 1153–1159. ISSN: 2397-334X. URL: https://doi.org/10.1038/s41559-017-0221-8.
Ngonghala, Calistus N., Mateusz M. Pluciński, Megan B. Murray, Paul E. Farmer, Christopher B. Barrett, Donald C. Keenan, and Matthew H. Bonds (Apr. 2014). "Poverty, Disease, and the Ecology of Complex Systems". In: *PLOS Biology* 12.4, pp. 1–9. URL: https://doi.org/10.1371/journal.pbio.1001827.
Njiru, M., M. Van Der Knaap, A. Taabu-Munyaho, C. S. Nyamweya, R. J. Kayanda, and B. E. Marshall (2014). "Management of Lake Victoria Dishery: Are We Looking for Easy Solutions?" In: *Aquatic Ecosystem Health & Management* 17.1, pp. 70–79. DOI: 10.1080/14634988.2014.881220.
Ogongo, Paul, Ruth K. Nyakundi, Gerald K. Chege, and Lucy Ochola (2022). "The Road to Elimination: Current State of Schistosomiasis Research and Progress Towards the End Game". In: *Frontiers in Immunology* 13. ISSN: 1664-3224. DOI: 10.3389/fimmu.2022.846108. URL: https://www.frontiersin.org/articles/10.3389/fimmu.2022.846108.
Pinot De Moira, Angela, Anthony J. C. Fulford, Narcis B. Kabatereine, Francis Kazibwe, John H. Ouma, David W. Dunne, and Mark Booth (2007). "Microgeographical and Tribal Variations in Water Contact and *Schistosoma mansoni* Exposure Within a Ugandan Fishing Community". In: *Tropical Medicine & International Health* 12.6, pp. 724–735. DOI: 10.1111/j.1365-3156.2007.01842.x.
Pluciński, Mateusz M., Calistus N. Ngonghala, Wayne M. Getz, and Matthew H. Bonds (2013). "Clusters of Poverty and Disease Emerge from Feedbacks on an Epidemiological Network". In: *Journal of The Royal Society Interface* 10.80, p. 20120656. DOI: 10.1098/rsif.2012.0656. URL: https://royalsocietypublishing.org/doi/abs/10.1098/rsif.2012.0656.
Rutten, Martine and Geoffrey Reed (2009). "A Comparative Analysis of Some Policy Options to Reduce Rationing in the UK's NHS: Lessons from a General Equilibrium Model Incorporating Positive Health Effects". In: *Journal of Health Economics* 28.1, pp. 221–233. ISSN: 0167-6296. DOI: 10.1016/j.jhealeco.2008.10.002. URL: http://www.sciencedirect.com/science/article/pii/S0167629608001380.
Secretariat, Lake Victoria Fisheries Organization (LVFO) (2016). *Fisheries Management Plan III (FMP III) for Lake Victoria Fisheries 2016-2020.* Tech. rep. Lake Victoria Fisheries Organization.

Smith, Martin D., John Lynham, James N. Sanchirico, and James A. Wilson (2010). "Political Economy of Marine Reserves: Understanding the Role of Opportunity Costs". In: *Proceedings of the National Academy of Sciences* 107.43, pp. 18300–18305. ISSN: 1091-6490. DOI: 10.1073/pnas.0907365107. URL: http://dx.doi.org/10.1073/pnas.0907365107.

Sokolow, Susanne H., Chelsea L. Wood, Isabel J. Jones, Kevin D. Lafferty, Armand M. Kuris, Michael H. Hsieh, and Giulio A. De Leo (Jan. 2018). "To Reduce the Global Burden of Human Schistosomiasis, Use 'Old Fashioned' Snail Control". In: *Trends Parasitol* 34.1. 29126819[pmid], pp. 23–40. ISSN: 1471-5007. DOI: 10.1016/j.pt.2017.10.002. URL: https://www.ncbi.nlm.nih.gov/pubmed/29126819.

Ssebuggwawo, V. and J. M. Kitamirike (2005). *Water Quality and Quantity Synthesis Final Report, LVEMP*. tech. rep. URL: https://www.mwe.go.ug/sites/default/files/library/Chapter%206%20Hydraulic%20Conditions.pdf.

Standley, Claire J., Moses Adriko, Moses Arinaitwe, Aaron Atuhaire, Francis Kazibwe, Alan Fenwick, Narcis B. Kabatereine, and J. Russell Stothard (2010). "Epidemiology and Control of Intestinal Schistosomiasis on the Sesse Islands, Uganda: Integrating Malacology and Parasitology to Tailor Local Treatment Recommendations". In: *Parasites & Vectors* 3.1, p. 64. DOI: 10.1186/1756-3305-3-64.

Stevens, Philip (2014). *Diseases of Poverty and the 10/90 Gap.* International Policy Network.

Sun, Le-Ping, Wei Wang, Yin-Ping Zuo, Qing-Biao Hong, Guang-Lin Du, Yu-Cai Ma, Jian Wang, Guo-Jing Yang, Dao-Jian Zhu, and You-Sheng Liang (Mar. 2017). "A Multidisciplinary, Integrated Approach for the Elimination of Schistosomiasis: A Longitudinal Study in a Historically Hyper-endemic Region in the Lower Reaches of the Yangtze River, China from 2005 to 2014". In: *Infectious Diseases of Poverty* 6.1, p. 56. ISSN: 2049-9957. DOI: 10.1186/s40249-017-0270-x. URL: https://doi.org/10.1186/s40249-017-0270-x.

Taylor, J. Edward and Mateusz J. Filipski, eds. (2014a). *Beyond Experiments in Development Economics: Local Economy-Wide Impact Evaluation.* Oxford: Oxford University Press.

– (2014b). "Evaluating the Impact of Global Food Price Shocks in Rural Guatemala". In: *Beyond Experiments in Development Economics: Local Economy-Wide Impact Evaluation.* Oxford University Press, pp. 166–180.

Taylor, J. Edward, Mateusz J. Filipski, Mohamad Alloush, Anubhab Gupta, Ruben Irvin Rojas Valdes, and Ernesto Gonzalez-Estrada (June 2016). "Economic Impact of Refugees". en. In: *Proc Natl Acad Sci U S A* 113.27, pp. 7449–7453.

Torres-Vitolas, Carlos A., Suzan C. M. Trienekens, Willemijn Zaadnoordijk, and Anouk N. Gouvras (May 2023). "Behaviour Change Interventions for the Control and Elimination of Schistosomiasis: A Systematic Review of Evidence from Low- and Middle-Income Countries". In: *PLOS Neglected Tropical Diseases* 17.5. Ed. by Alberto Novaes Ramos, e0011315. ISSN: 1935-2735. DOI: 10.1371/journal.pntd.0011315. URL: http://dx.doi.org/10.1371/journal.pntd.0011315.

Tukahebwa, Edridah M., Pascal Magnussen, Henry Madsen, Narcis B. Kabatereine, Fred Nuwaha, Shona Wilson, and Birgitte J. Vennervald (July 2013). "A Very High Infection Intensity of Schistosoma mansoni in a Ugandan Lake Victoria Fishing Community Is Required for Association with Highly Prevalent Organ Related Morbidity". In: *PLOS*

Neglected Tropical Diseases 7.7, pp. 1–8. DOI: 10.1371/journal.pntd.0002268. URL: https://doi.org/10.1371/journal.pntd.0002268.

Unicef (2022). *Primary Education Data – Out of School Rates*. URL: https://data.unicef.org/topic/education/primary-education/.

Vale, Nuno, Maria João Gouveia, Gabriel Rinaldi, Paul J. Brindley, Fátima Gärtner, and José M. Correia da Costa (Apr. 2017). "Praziquantel for Schistosomiasis: Single-Drug Metabolism Revisited, Mode of Action, and Resistance". In: *Antimicrob Agents Chemother* 61.5. 28264841[pmid], e02582–16. ISSN: 1098-6596. DOI: 10.1128/AAC.02582-16. URL: https://www.ncbi.nlm.nih.gov/pubmed/28264841.

Verikios, George, Peter B. Dixon, Maureen T. Rimmer, and Anthony H. Harris (2013). *The Impact of Changes in Health Status: An Economywide Analysis for Australia*. Tech. rep. Monash University.

Watts, Susan and Samiha El Katsha (1997). "Irrigation, Farming and Schistosomiasis: A Case Study in the Nile Delta". In: *International Journal of Environmental Health Research* 7.2, pp. 101–113. DOI: 10.1080/09603129773896.

Wilen, James E. (Sept. 2013). "The Challenges of Pro-Poor Fisheries Reform". In: *Marine Resource Economics* 28.3, pp. 203–220. ISSN: 2334-5985. DOI: 10.5950/0738-1360-28.3.203. URL: http://dx.doi.org/10.5950/0738-1360-28.3.203.

Witte, Frans, Tijs Goldschmidt, Jan Wanink, Martien van Oijen, Kees Goudswaard, Els Witte-Maas, and Niels Bouton (May 1992). "The Destruction of an Endemic Species Flock: Quantitative Data on the Decline of the Haplochromine Cichlids of Lake Victoria". In: *Environmental Biology of Fishes* 34.1, pp. 1–28. ISSN: 1573-5133. DOI: 10.1007/BF00004782. URL: https://doi.org/10.1007/BF00004782.

World Bank (2022). *Compulsory education, duration (years) - Sub-Saharan Africa*. Data retrieved from World Development Indicators, URL: https://data.worldbank.org/indicator/SE.COM.DURS?locations=ZG.

World Health Organization (2015). "Schistosomiasis: Number of People Treated Worldwide in 2013". In: *Weekly Epidemiol Rec.* 90.5, pp. 25–32. URL: https://www.who.int/wer/2015/wer9005.pdf.

Chapter 2

The Epi-Bio-LEWIE Model

2.1 Introduction

My research offers a novel coupling of an epidemiological (Epi) model of infection dynamics, a biological (Bio) model of fish population dynamics, and a computable general-equilibrium (CGE) model of the local economy. In this study, I refer to the coupled model as the Epi-Bio-LEWIE (EBL) model. The component models of the EBL model characterize three distinct yet interconnected domains of the human-natural environment.

The public health domain of the human-natural environment is represented by the Epi component, which builds upon previous studies that incorporate the disease dynamics of NTDs, including Schistosomiasis (referred to as Schisto below). To characterize the link between economic activity and prevalence of the disease, I draw from the methodologies found in Garchitorena et al. (2017) and similar studies that model system parameters as a function of economic activity. I also incorporate methods found in Mari et al. (2017) to characterize the dynamics of the disease Schisto while accounting for heterogeneity in risks for exposure to the disease across subsets of the population.

The ecological domain of the human-natural environment is represented by the Bio com-

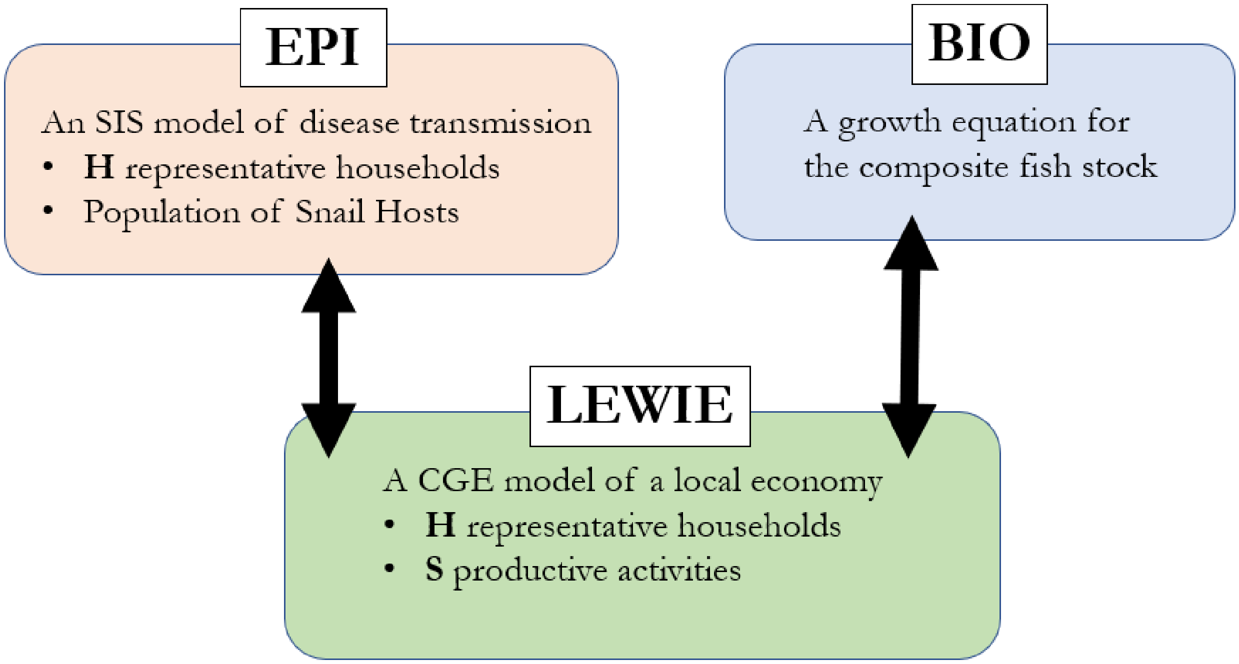


Figure 2.1: A conceptual representation of the EBL model.

ponent, which follows previous studies that focus on the linkages between local economies and a biological population, such as a stock of fish (e.g., Gilliland, Sanchirico, and Taylor, 2019). In many settings where Schisto is prevalent, the main economic activity associated with disease transmission is rice production or fishing. For the local economy under study, fishing is a primary economic activity and an activity associated with the transmission of the disease. By including the Bio model component, I account for the important dynamic relationship between fishing effort, disease prevalence, and the stock of fish.

The economic domain of the human-natural environment is represented by the CGE component, which models the impacts that policies, programs, or other types of an exogenous shock may have on the economic participants, such as households or businesses. The CGE modeling approach is commonly applied at the national economy scale (Lofgren, Harris, and Robinson, 2002). However, previous studies have downscaled the application of this modeling approach to include local economies composed of village clusters (Filipski and Belton, 2018), specially defined areas such as refugee camps (Taylor, Filipski, et al., 2016), or groups of villages with a high degree of economic interaction with nearby natural protected areas (World Bank, 2021). Given that I focus on a local economy in this study, I refer to the CGE component as the LEWIE component.[1]

I use the EBL model to evaluate the impact of policy shocks over a study period of ten years. To do this, I prepare the EBL model for analysis by finding the baseline solutions such that the EBL model is in equilibrium within each component model and between component models. At baseline, I assume that the local economy, the disease dynamics, and the population of the fish stock targeted by local fishers are at their steady-state levels. This assumption implies that absent any exogenous shock to the model, the baseline solution values would remain unchanged over the 10-year study period.

In the next section, I describe the three component models of the EBL model and discuss how the component models are connected. I then describe how I use original survey data to construct a representation of the households and economic activities of the local economy. I follow this with a description of how parameter values are assigned to the EBL model and, subsequently, how I prepare the model for analysis. I conclude the chapter by explaining how I use the EBL model to simulate the impact of policy shocks over the study period.

2.2 The LEWIE Component

I consider a model of a local economy with H representative households, or household types, that engage in S productive activities, one of which is fishing in an open-access lake. The parasite that causes the disease Schisto is present in the lake. Infection with the disease Schisto reduces the effectiveness of labor employed in the local economy (Audibert and Etard, 1998; Audibert and Etard, 2003). I assume that household population shares and the total population in the local economy are fixed.

[1] LEWIE, which stands for Local Economy Wide Impact Evaluation, is an acronym that refers to the type of model used in this study and in previous studies (e.g., Taylor and Filipski, 2014a)

2.2.1 Production Functions

Producers in the local economy employ effective labor E and capital K as inputs in the production of output QP. For the fishing sector, production can be written as

$$QP_{fish} = F_{fish}(E_{fish}, K_{fish}, X) \tag{2.1}$$

where the stock of fish, denoted as X, enters into production as an input alongside labor and capital. I assume that the production function $F_{fish}(\cdot)$ is concave and increasing in each input, as in a conventional bio-economic model.

Under perfect competition, equilibrium conditions require that the marginal value product of an input in one sector equals the marginal value product of that same input in another sector. However, the open-access nature of the fishing reservoir in this example results in a market failure in which labor is over-allocated to the fishing sector (Manning, Taylor, and Wilen, 2018). This occurs because fishers do not fully account for the impact that their production has on future production via the stock of fish, which in a completely open-access setting is costless (ignoring search costs) for the fisher in the sense that no market price exists for the stock of fish in the lake. Consequently, the value of the contribution from the stock of fish in the production process is distributed among the non-stock inputs, E_{fish} and K_{fish} (Manning, Taylor, and Wilen, 2018; Lindsay et al., 2020).

We can observe how the non-stock inputs capture the value of the fish stock's contribution to production by applying Euler's theorem to Eq. (2.1) and obtaining

$$p_{fish}QP_{fish} = \frac{p_{fish}}{\omega}\frac{\partial F_{fish}(\cdot)}{\partial E_{fish}}E_{fish} + \frac{p_{fish}}{\omega}\frac{\partial F_{fish}(\cdot)}{\partial K_{fish}}K_{fish} + \frac{p_{fish}}{\omega}\frac{\partial F_{fish}(\cdot)}{\partial X}X \tag{2.2}$$

after multiplying both sides by output price p_{fish}. Equation (2.2) states that for a homogeneous production function of degree ω, the total value of production is equal to the sum of the marginal value product of each input multiplied by the number of units of the input employed in the production process. We can rewrite Eq. (2.2) as

$$
\begin{aligned}
p_{fish}QP_{fish} =& \frac{p_{fish}}{\omega}\left[E_{fish}\frac{\partial F_{fish}(\cdot)}{\partial E_{fish}} + \theta X\frac{\partial F_{fish}(\cdot)}{\partial X}\right] + \\
& \frac{p_{fish}}{\omega}\left[K_{fish}\frac{\partial F_{fish}(\cdot)}{\partial K_{fish}} + (1-\theta)X\frac{\partial F_{fish}(\cdot)}{\partial X}\right]
\end{aligned}
\tag{2.3}
$$

where θ and $1-\theta$ represent the shares of the value that the fish stock contributes in the production process that is captured by effective labor and capital, respectively.

For all other sectors, output $QP_{s'}$ can be written as a function of labor and capital

$$
QP_{s'} = F_{s'}(E_{s'}, K_{s'}) \tag{2.4}
$$

where production in the other $S-1$ sectors is denoted using the subscript s'. I assume the production function $F_{s'}(\cdot)$ is homogeneous of degree one, concave, and increasing in both inputs. By applying Euler's theorem to Eq. (2.4), we can obtain

$$
p_{s'}QP_{s'} = p_{s'}\frac{\partial F_{s'}(\cdot)}{\partial E_{s'}}E_{s'} + p_{s'}\frac{\partial F_{s'}(\cdot)}{\partial K_{s'}}K_{s'} \tag{2.5}
$$

after multiplying both sides by the output price, $p_{s'}$. Equation (2.5) states that the total value of production is equal to the sum of the marginal value product of each input multiplied by the number of units of the input employed in the production process. Under perfect competition, each input is paid a wage equal to the value created by the last unit employed. In sector s', it is true that effective labor is paid a wage equal to its marginal value product, and similarly for capital. Consequently, Eq. (2.5) can be rewritten as

$$
p_{s'}QP_{s'} = wE_{s'} + rK_{s'} \tag{2.6}
$$

with w and r representing the wages paid to effective labor and capital, respectively. Equation (2.6) states that total revenue from production equals the total cost of production, which is true for the profit-maximizing firm operating under perfect competition.

In order for wages to equalize across sectors under perfect competition, the marginal value of an input's contribution toward output must equalize across sectors. For the fishing sector, the marginal value of a non-stock input's contribution toward output is the sum of that input's marginal value product *and* the input's share of the fish stock's contribution to output, the latter distributed equally in the case of a homogeneous supply of the input. For effective labor and capital,

$$w = p_{s'} \frac{\partial F_{s'}(\cdot)}{\partial E_{s'}} = \frac{p_{fish}}{\omega} \left[\frac{\partial F_{fish}(\cdot)}{\partial E_{fish}} + \theta \frac{X}{E_{fish}} \frac{\partial F_{fish}(\cdot)}{\partial X} \right] \tag{2.7}$$

$$r = p_{s'} \frac{\partial F_{s'}(\cdot)}{\partial K_{s'}} = \frac{p_{fish}}{\omega} \left[\frac{\partial F_{fish}(\cdot)}{\partial K_{fish}} + (1-\theta) \frac{X}{K_{fish}} \frac{\partial F_{fish}(\cdot)}{\partial X} \right] \tag{2.8}$$

across all sectors. Since the second term within the brackets on the right side in each of the two preceding equations is positive, it must be the case that the marginal value product of effective labor (or capital) in the fishing sector is less than that of the other sectors. Since $F_{fish}(\cdot)$ is concave, this can occur only if an excessive amount of labor (or capital) is employed in the fishing sector.

2.2.2 Effective Labor and Labor Time

Fishing occurs in a lake where the parasite that causes the disease Schisto is prevalent. Direct exposure to the lake water can result in infection, which reduces the effectiveness of labor time supplied by households to the local economy. Consequently, the amount of effective labor supplied by household h depends on the amount of labor time that it supplies, L_h, and its infection rate I_h.

I define a time-invariant parameter $\alpha \in [0, 1]$ that represents the impact that Schisto infection has on the ability to work. Previous studies with focus on Schisto provide evidence that α may range between 0.05 and 0.3 (Audibert and Etard, 1998; Audibert and Etard, 2003; Barbosa and Costa, 1981; Kamel et al., 2002). I assume a value of 0.15 in the main analysis. In Chapter 5, I investigate the sensitivity of the main results to different values of α.

I assume that infection status can take two values: either infected or not infected.[2] For the proportion of the representative household that is infected, the quantity of labor time supplied to any sector is reduced by $\alpha\%$. For the remaining proportion of the household, the quantity of effective labor supplied is equal to the quantity of labor time supplied by the household. Given the two states of infection status,

$$E_h = I_h(1-\alpha)L_h + (1-I_h)L_h = L_h(1-\alpha I_h) \tag{2.9}$$

represents the relationship between effective labor and labor time. In this study, I do not explicitly model the labor-leisure trade-off made by the household. Instead, the household supply of labor time depends on the wage rate and the elasticity of the labor supply. Consequently, the supply of effective labor can vary with changes in infection rates as well as in response to changes in the wage.

2.2.3 Household Expenditures and Imported Goods

A representative household earns income from employing its endowment of factors of production at the prevailing market wage rates, and it purchases output from both sectors of the economy at prevailing output prices. I model the utility that a household gets from consumption using a constant elasticity of substitution function, which drives the household to substitute between goods in response to changes in relative prices over time.

In response to changes in local prices, a representative household can imperfectly substitute

[2]Although I abstract from the role that intensity of infection may play within this framework, the intensity of Schisto infection can vary across infection status, with chronic infection leading to worse consequences as discussed in the background section on the disease (King et al., 2006; Gray et al., 2011).

its purchases of output produced locally with imports. I follow previous approaches to CGE modeling by employing an Armington function to represent the share of goods demanded as imports in a sector (Gilliland, Sanchirico, and Taylor, 2019). The Armington function combines demand for locally produced goods and imports of the same good into a composite good according to a specified substitution elasticity between the two sources and a share of the composite good that is demanded locally (Armington, 1969).

2.3 The Epi Component

The Epi component of the EBL model draws from the compartmental modeling methodology in Castonguay et al. (2020), Mari et al. (2017), and Garchitorena et al. (2017). I assume that the human population is divided into H subpopulations that correspond to the H representative households in the local economy. I also assume that the total population in the local economy and the household population shares are fixed, and that the H subpopulations are closed, which means that a member of one group cannot switch to another group. For example, a poor fishing household cannot change to become a poor nonfishing household. I assume no immunity following infection for either the snail or human populations, which is consistent with previous literature (Mari et al., 2017; Castonguay et al., 2020). This means that the members of the human and snail populations are either susceptible or infected, with no possibility of developing immunity.

2.3.1 State Equations

The state equation for household h's infection rate can be written as

$$\dot{I}_h = \beta \tau_h^E \epsilon_h^E Y (1 - I_h) - \gamma I_h \tag{2.10}$$

where I_h denotes the infection rate for household h and Y denotes the infection rate for the host snail population in the single water source. For household h, transition into the infected classification is determined by: Y, the susceptible portion of the household $(1 - I_h)$, the snail-to-human transmission rate parameter β, a household-specific measure of exposure time τ_h^E, and a household-specific exposure-risk parameter ϵ_h^E (Mari et al., 2017). Transition out of the infected classification is determined by the parameter γ, which is defined as the mortality rate of the parasite in the human host.

The state equation for the infected share of the snail population can be written as

$$\dot{Y} = \chi(1 - Y) \sum_{h=1}^{H} g_h \tau_h^C \epsilon_h^C I_h - \mu Y \tag{2.11}$$

where the transition of the snail population from susceptible to infected is determined by: the size of the susceptible proportion $(1 - Y)$; the human-to-snail transmission rate parameter χ; and a weighted sum of the infection rates of the H households. The weighted sum of household infection rates in (2.11) is calculated using household population shares, g_h, household-specific measures of contamination risk, ϵ_h^C, and a household-specific measure of contamination time τ_h^C (Mari et al., 2017). For the snail population, transition out of the infected classification is determined by the parameter μ, which is defined as the mortality rate of the parasite in the snail host.

2.3.2 Equilibria and R_0

The system of disease dynamics described by Eqs. (2.10) and (2.11) yields two steady-state equilibrium points. "Steady-state" refers to the fact that both $\dot{I}_h$ and $\dot{Y}$ are equal to zero over time at these equilibrium points. The Disease-Free Equilibrium (DFE) is characterized by zero values of the state variables I_h and Y. The Endemic Equilibrium (EE) is characterized by positive values of the same state variables.

At most one of these two equilibrium points can be stable for a given set of parameter values. The stability of either equilibrium point can be determined by the value of the community-level reproduction number, R_0, a dimensionless value that is defined as the average number of secondary cases across subpopulation groups arising from one new infection when the entire population is susceptible (Diekmann, Heesterbeek, and Roberts, 2009). Since R_0 is defined in terms of an average across the different groups in a population, R_0 is unique to the system of disease dynamics and common across subpopulation groups (households and snails).

Following the methodology of Diekmann, Heesterbeek, and Roberts (2009) and the applications thereof in Garchitorena et al. (2017) and Castonguay et al. (2020), I calculate R_0 as the dominant eigenvalue of the next-generation matrix for the above system of disease dynamics (see Appendix 2.B for a detailed description of the process used to derive R_0). For a local economy with H households, this matrix can be written as $\mathcal{F}\mathcal{V}^{-1}$, where

$$\mathcal{F} = \begin{bmatrix} 0 & \dots & 0 & \beta\tau_1^E\epsilon_1^E \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & 0 & \beta\tau_H^E\epsilon_H^E \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad \text{and} \quad \mathcal{V} = \begin{bmatrix} -\gamma & \dots & 0 & 0 \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & -\gamma & 0 \\ \chi g_1\tau_1^C\epsilon_1^C & \dots & \chi g_H\tau_H^C\epsilon_H^C & -\mu \end{bmatrix} .$$

The R_0 of the system described by Eqs. (2.10) and (2.11) can be written as

$$R_0 = \frac{\beta\chi\sum_{h=1}^{H} g_h\tau_h^E\tau_h^C\epsilon_h^E\epsilon_h^C}{\mu\gamma} . \tag{2.12}$$

When $R_0 < 1$, the DFE is stable and the values for the state variables I_h and Y will trend toward zero. When $R_0 > 1$, the EE is stable and the state variables I_h and Y will trend toward their respective EE values as determined by the system's parameter values.

2.3.3 Time-Varying Epi Parameters

I express three of the Epi parameters as functions of economic activity in order to model the impact that decisions in the local economy have on disease dynamics. I focus on two measures of economy activity: aggregate output Z, which is a proxy measure of the capacity for *public* investment in disease prevention and treatment, and exposure time to the disease τ_h, which accounts for *private* decisions that are directly correlated with transmission of the disease.

I model the exposure rate parameter β as a *decreasing* function of aggregate output Z. I define β as

$$\beta(Z) = \phi_\beta(Z)[\beta_{max} - \beta_{min}] + \beta_{min} \tag{2.13}$$

where $\phi_\beta(Z)$ is decreasing in Z and determines the relative weights for the assigned minimum and maximum values of the exposure-rate parameter. As Z increases, $\phi_\beta(Z)$ declines, shifting the relative importance in (2.13) to β_{min}, which results in a decline in the value of β. This modeling choice reflects the view that higher levels of aggregate output can result in additional public investment in disease prevention (Bonds et al., 2010), which could reduce the impact that a unit of exposure time has on disease transmission. I define $\phi_\beta(Z)$ using a sigmoid function

$$\phi_\beta(Z) = \frac{1}{1 + \exp\left(\frac{Z - Z_{med}}{Z_{slope}}\right)} \tag{2.14}$$

which reflects rapid change in value around the median and slower change in value closer to the assigned minimum and maximum values (El Aferni, Guettari, and Tajouri, 2020). Intuitively, we can anticipate that at low levels of disease prevalence, a one unit change in a factor such as exposure time will have little impact on disease prevalence because the number of infected cases is small and thus the likelihood of transfer from infected to susceptible is small, all else equal. As the number of infected cases increases, a unit of exposure time would have a larger impact on disease prevalence, but only to a point, after which saturation would set in. At high levels of disease prevalence, the number of susceptible cases is small, which means the potential for an additional infection to occur is also small for a one unit change of exposure time.

Similarly, I define γ as

$$\gamma(Z) = \phi_\gamma(Z)[\gamma_{max} - \gamma_{min}] + \gamma_{min} \tag{2.15}$$

where $\phi_\gamma(Z)$ is also defined using a sigmoid function, written as

$$\phi_\gamma(Z) = \frac{1}{1 + \exp\left(\frac{-(Z - Z_{med})}{Z_{slope}}\right)} \tag{2.16}$$

and where $\phi_\gamma(Z)$ is increasing in Z. As with $\beta(Z)$, $\phi_\gamma(Z)$ determines the relative importance for the assigned minimum and maximum values for γ. In contrast to Eq. (2.14), the denominator in Eq. (2.16) *declines* in value as Z increases (note the negative sign in the numerator of the exponentiated fraction). An increase in Z shifts the weight in (2.15) to γ_{max}, resulting in an increase in the value of γ. This modeling choice reflects the view that higher levels of aggregate output can lead to additional public investment in disease treatment (Bonds et al., 2010).

2.4 The Bio Component

Following previous literature, I model the fish stock as a composite of the three main species targeted by fishers in the local economy (Kateregga and Sterner, 2009). The price per kilo for the Nile Perch is the highest among the three species. Tilapia is harvested in both the open waters and in the nascent aquaculture industry in the region. The *mukene* silverfish is an important source of food for households and for livestock.

I model the natural growth process of the composite fish stock using a logistic growth function. The state equation for the composite fish stock X is

$$\dot{X} = f(X) = X r_{fstock}(1 - \frac{X}{K_{lake}}) - HARV \tag{2.17}$$

where r_{fstock} is the annual growth rate for the composite fish stock and K_{lake} is the carrying capacity for the fishing reservoir, as is common in the fishery economics literature (Downing et al., 2013; Manning, Taylor, and Wilen, 2018; Gilliland, Sanchirico, and Taylor, 2019). The stock of fish is stable over time whenever total output in the fishing sector, $HARV$, is equal to the growth of the fish stock for the same time period.

2.5 Links Between Model Components

The three domains within the human-natural environment are linked together in four distinct ways. As a consequence of these linkages, policies that are designed to have a direct impact in one domain may have ancillary consequences—either benefits or costs—in the other domains.

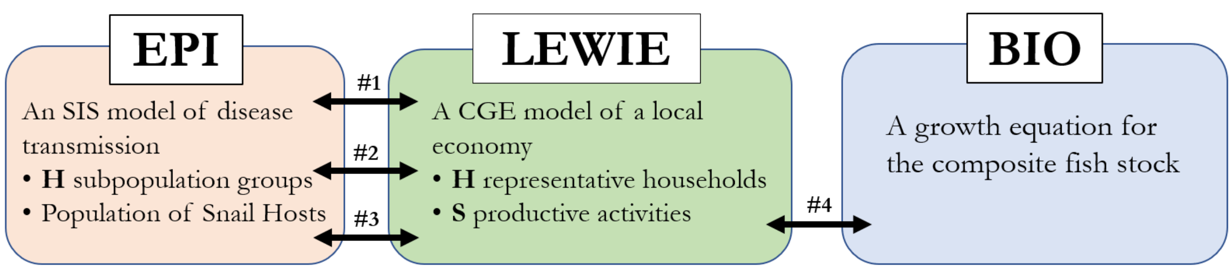


Figure 2.2: A Conceptual representation of the EBL model. Black arrows identify the four direct links between the components.

Link #1: Aggregate Output

By writing the exposure-rate parameter, β, and the parasite-human host mortality rate parameter, γ, as functions of aggregate output Z (see Eqs. (2.13) and (2.15)), I account for the role of *public* investment in disease prevention and treatment (Bonds et al., 2010; Garchitorena et al., 2017). The motivation for this modeling choice is the recognition that aggregate income provides capacity for *public* investment that can target both treatment and prevention of diseases such as Schisto. Such community-wide investments may take the form of personal protective equipment such as fishing waders, preventative or curative treatments for the disease, or infrastructure investments resulting in improved access to clean water, sanitation, and hygiene (WASH) facilities.

Link #2: Exposure Time

The second link between the disease and the local economy is represented by the novel inclusion of τ_h, a household-specific measure of exposure time to the disease, in the Epi component. While multiple transmission pathways exist for Schisto, not all are directly connected to the economic activity represented in the EBL model. Consequently, the parameter τ_h found in Eqs. (2.10) and (2.11) consists of a time-invariant component, which includes background economic activities such as time spent collecting water, cleaning, and recreating, and a time-varying component, which is composed of commercial fishing labor time (i.e., labor demanded by the fishing sector in the local economy). The activities that comprise the time-invariant component are not modeled as functions of the local economy or natural environment and therefore do not respond to changes in the model. Nevertheless, these activities are primary sources of exposure time to the disease and thus are accounted for in this study (King et al., 2006; World Health Organization, 2022).

However, quantities of labor demanded across activities may vary in response to changes in the human-natural environment. Consequently, the time-varying component of the parameter τ_h accounts for the fact that changes in demand for labor in the fishing sector translate to changes in exposure time at the household level, which has consequences for disease transmission and thus future disease prevalence. Still, the degree to which change in the time-varying component of τ affects future disease prevalence in the model is mitigated by the time-invariant component of τ, the effect of which can be significant in areas where Schisto is prevalent.

Link #3: Effective Labor and Labor Time

Whereas the first two links symbolize how household infection rates can be affected by changes in measures of economic activity, link #3 captures how changes in household infection rates can feed back into the economy. In the EBL model, the supply of effective labor depends on household infection status (see Eq. (2.9)). Consequently, if household infection rates decline, the supply of effective labor will increase, *ceteris paribus*, resulting in an increase in output and household incomes. Furthermore, depending on what drives the changes in household infection rates—i.e., the relative importance of the first two links—one might observe heterogeneous changes in quantities of labor supplied by households.

Link #4: Total Harvest and the Fish Stock

The fourth direct link between the components of the EBL model is found in Eq. (2.17), wherein total harvest in the fishing sector draws down the future stock of fish. This implies that the size of the future stock of fish is *decreasing* in the amount of effective labor employed in the fishing sector. Consequently, changes in the fishing sector, such as an increase in harvest due to rising household incomes (and thus demand for fish), can create pressure on future stocks of fish.

Further, we can see that the size of the fish stock is a decreasing function of the prevalence of the disease by first recalling that the amount of fish harvested by household h depends on effective labor E_h, other non-resource inputs such as capital, and the fish stock X (see Eq. (2.19)). As a thought experiment, an increase in I_h while holding constant other factors, such as quantity of fishing labor time supplied by household h, would result in a decline in the amount of fish harvested by household h, since E_h is decreasing in I_h. Summing harvest across households, we can conclude that the total harvest, $HARV$, is decreasing in household infection rates. On first glance, this relationship suggests that a healthier population of workers would lead to an increase in pressure on future fish stocks, all else equal. Perversely, higher rates of Schisto prevalence in the population may prop up the level of the fish stock, which is consistent with previous research on fishing effort and disease (Fiorella et al., 2017).

2.6 Household Types and Economic Sectors

The economic component of the EBL model is designed to characterize the consumption and production activities of representative households in the local economy. Similar to previous studies that use this modeling approach (e.g., Taylor and Filipski, 2014a), the empirical model in this study consists of production functions for each sector of the economy, intermediate input demands, factor demands for each factor employed in each sector, household consumption and income, market-clearing equations for goods and both tradeable and non-tradeable factors, and Armington functions for imported goods. The model is solved when the equilibrium conditions are satisfied. Additionally, the LEWIE component used in this study includes an equilibrium condition that accounts for the role that Schisto infection plays in determining the supply of effective labor.

Using microdata on households and businesses in my study area, I classify households into four representative groups that participate in six productive activities.

2.6.1 Household Survey Data

The survey data used for this study was collected in 2017 by a team of researchers from the Ugandan Ministry of Agriculture (MAAIF), the International Fund for Agricultural Development, and the University of California-Davis. The survey was conducted on Bugala Island in Kalangala District, Uganda. Bugala Island is the largest and most populated island in the district. The district government and the vast majority of businesses in the district are located on Bugala island.

A team of 14 local enumerators were trained over a period of 5 days, including two half-days

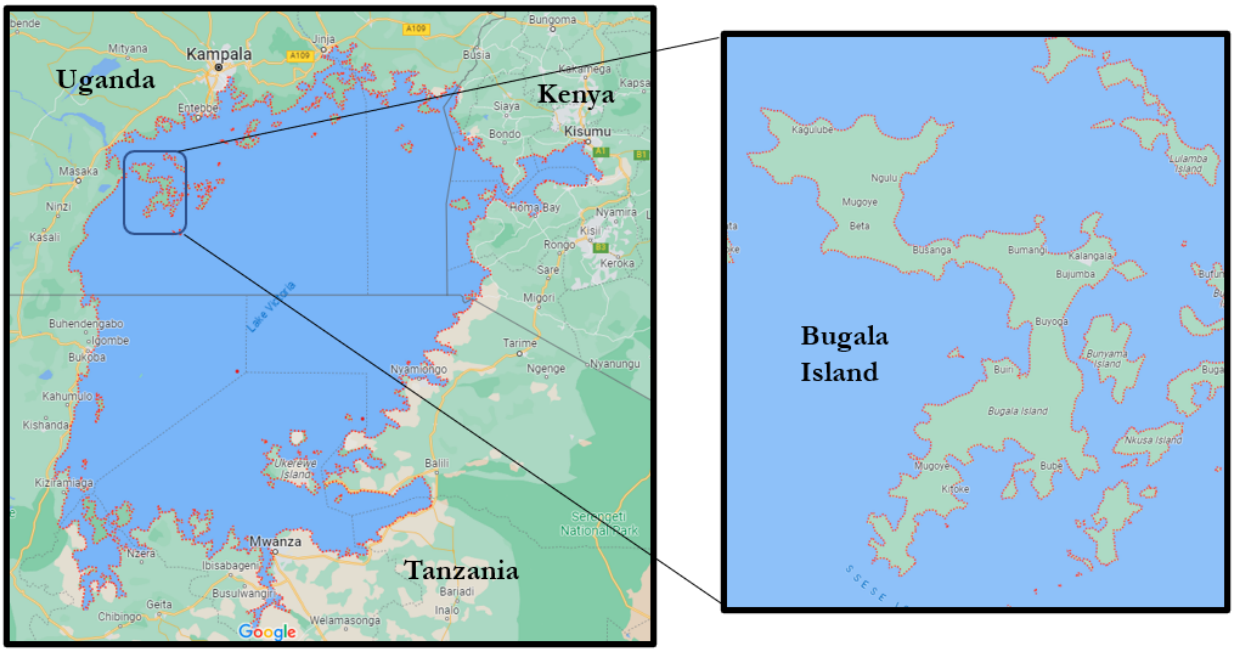


Figure 2.3: Map of Lake Victoria with bordering countries. Inset map showing location of Bugala Island in Lake Victoria. Produced using *QGIS ver.* 3.22.14.

of pilot-testing combined with training. A total of 511 households and 284 businesses in 39 villages were interviewed over a period of 3 weeks. Villages were randomly selected from a list of village names provided by the district government. Within each village, households were randomly selected from a list provided by village leaders. Without a master business list, enumerators were instructed to interview all businesses that consented and had not participated in the household survey. The business interview took approximately 15 minutes, and business owners were encouraged to pause the interview as needed so that business operations were not interrupted. Overall, less than 1% of households and businesses did not consent to interviews.

The survey questions were designed to gather detailed information on the household consumption and production activities of households and businesses on the island. The household survey consisted of several modules:

- An individual roster included questions related to education, health, employment and time-use questions.

- A household-level expenditure module contained questions about consumption and point of purchase for: purchases within the past two weeks (e.g., food items and services such as bars, restaurants, and transportation), purchases within the past month (e.g., utilities and fuel), and purchases within the past year for less frequent purchases (e.g., home maintenance and repair).

- Additional household-level modules included questions on dwelling characteristics, assets, and savings and remittances.

The household survey also included one module for each of the productive activities in the local economy: fishing, oil palm, other crops, livestock, and household-run businesses, along with a filter question asking whether or not the household participated in the activity. Each production module included questions on output levels, input use, and other costs of production. To ensure data compatibility, the questions in the business survey were identical to the questions used in the business module in the household survey. Further details of the data collection effort can be found in Taylor, Whitney, and Zhu (2019).

2.6.2 Defining Representative Households

Using the survey data, I define four household types, or representative households, by classifying households in the survey data as either fishing or non-fishing, and as either poor or nonpoor. To classify fishing households, I rely on the initial screening question for the interview, which asks whether anyone in the household has engaged in fishing activities in the past 12 months.

To define poverty status, I use data from the household consumption module of the survey to calculate per capita consumption for each household. Ideally, I would define household poverty status using a measure of income for each household that could be constructed with the survey data. However, self-reported consumption data is widely regarded as more reliable than self-reported data on income, since the latter is more prone to errors resulting from either under- or over-reporting. I then define a daily per capita poverty line of $1.04, converted to a local currency amount of 3744 UGX using the exchange rate at the time of survey enumeration, and use this to assign poverty status to households with per capita consumption at or below this poverty line.[3] Table 2.1 shows summary statistics for sample households by classification.

Table 2.1: Summary Statistics for the Four Household Types

Household (Observations)	Household Size	Age of Household Head (Years)	Dependency Ratio	Expenditures	Education, Household Head (Years)
Poor, Fishing	5.2	40.4	0.399	2,426	7.3
(n=14)	(2.4)	(10)	(0.254)	(856)	(4.0)
Nonpoor, Fishing	4.4	38	0.39	10,980	7.7
(n=70)	(2.5)	(11.1)	(0.231)	(6,173)	(4.2)
Poor, Nonfishing	5.1	42	0.495	2,225	6.7
(n=172)	(2.7)	(13.7)	(0.247)	(852)	(4.5)
Nonpoor, Nonfishing	3.3	37.9	0.304	9,399	8.6
(n=255)	(2.1)	(12.3)	(0.286)	(5,639)	(4.2)
Total	4.1	39.4	0.382	6,816	7.8
(n=511)	(2.5)	(12.7)	(0.278)	(5,791)	(4.4)

Notes: Averages for each measure are reported with standard deviations in parentheses. Daily per capita expenditures are reported in Ugandan Shillings. Source: Original data.

Based on the daily per capita poverty line described above, the poverty rate among households in the local economy is 36.4%. Poorer households reported having a larger average

[3]This poverty line is in line with the national poverty line for Uganda, and well below the international poverty line of $1.90 per day established by the World Bank in 2015 (Bank, 2016). In Chapter 5 I test how sensitive my results are to alternative values of this poverty line.

household size and older average age of the household head. Fishing households reported slightly higher expenditures than their nonfishing counterparts. These (small) differences are suggestive evidence that fishers may receive compensation in the form of more income for time spent working in a sector where risks of illness due to Schisto, AIDS, alcoholism, and other illnesses accompany the dangers associated with fishing in the lake. Differences across dependency ratios, which is defined here as the number of non-income earners divided by household size, suggest that poor households rely on a relatively smaller number of income earners in their households. Approximately 16% of the households reported that they participated in fishing activities in the 12 months preceding the interview. When compared to results from previous studies using national census data, this number is likely an underestimate of the number of households who actually participate in the fishing sector. For example, using 2014 national census data Ssemmanda and Opige (2019) report that approximately 60% of the population of Kalangala District participated in some aspect of the fishing sector value chain.

2.6.3 Defining Productive Sectors

Information was collected for the six productive activities in the local economy: fishing, oil palm crops, food crops, livestock, and the service and retail business sectors. Oil palm crops are separated from other agriculture due to the relatively unique production process of this cash crop. Similarly, fishing is identified as a separate activity due to its unique production process, which includes harvest of a renewable natural resource. Food crop production in the local economy consists of rice, *matoke* (a delicious banana for cooking), cassava, maize, and other vegetables and fruits. Livestock production in the local economy consists mainly of cattle, poultry, goats, and pigs. Common businesses in the local service sector include bars and restaurants, barbers and hairdressers, and food processors. Grocery shops, corner shops and petty traders make up a majority of the retail businesses in the local economy. Subsistence farming is a common trait among households in the district, with approximately

65% of the labor force engaged in the activity as of the 2014 census (UBOS, 2017).

Table 2.2: Household Participation by Sector

Household (Observations)	Oil Palm	Food Crops	Livestock	Fishing	Retail	Service
Poor, Fishing (n=14)	21.4%	50.0%	78.6%	100.0%	42.9%	28.6%
Nonpoor, Fishing (n=70)	24.3%	65.7%	74.3%	100.0%	15.7%	42.9%
Poor, Non-Fishing (n=172)	25.6%	59.9%	51.7%	0.0%	37.2%	23.8%
Nonpoor, Non-Fishing (n=255)	27.1%	47.5%	50.6%	0.0%	45.9%	36.9%

Source: Original data.

2.7 Estimating Parameter Values for the LEWIE Component

I specify functional forms for the equations in the LEWIE component and use the original household survey data to estimate them. For the parameters that I cannot estimate using the household data, I use values from the literature and, where applicable, undertake sensitivity analysis. In the text below, time-varying parameters have a t subscript. All other parameter values are fixed over the study period.

2.7.1 Production Functions

For the non-fishing sectors, I use a Cobb-Douglas production function to represent the relationship between the J final inputs used in the production process and final output. The production functions for the non-fishing sectors can be written as

$$QP_{s,t} = A_s \prod_{j=1}^{J} {f_{j,s,t}}^{\delta_{j,s}} \tag{2.18}$$

where $QP_{s,t}$ is the total output produced in sector s in time t. A_s is a time-invariant total factor productivity (TFP) shift parameter. The parameter $f_{j,s,t}$ represents the amount of final input j used for production in sector s at time t. The exponent $\delta_{j,s}$ is the time-invariant output elasticity for final input j. I assume constant returns to scale in each of the non-fishing sectors. This means that $\delta_{j,s}$ is also the share of output attributable to final input j and that the sum of these output shares in each of the non-fishing sectors is

$$\sum_{j=1}^{J} \delta_{j,s} = 1 \ .$$

Production in the fishing sector is also modeled using a Cobb-Douglas production function. Accounting for the role that the fish stock plays in the fishing sector, I write the production function for this sector as

$$QP_{fish,t} = A_{fish} \prod_{j=1}^{J} f_{j,fish,t}^{\delta_{j,fish}} X_t^{\delta_{fstock}} \ . \tag{2.19}$$

In contrast to the other productive sectors, I do not assume constant returns to scale in all inputs. Following previous literature, I assume that returns to scale for all inputs *except the fish stock* are constant, and I assume a value of 0.645 for the output elasticity of the fish stock (Gilliland et al., forthcoming).

2.7.2 Intermediate Demands and Value-Added Output Price

Intermediate inputs are used in several of the productive sectors in the local economy. Examples include output from crop and livestock production that are used as inputs in production for the retail and service sectors. Following previous studies, I model demand for intermediate goods using a Leontief production function (Taylor and Filipski, 2014a). This means that 1) there is no substitution among intermediate inputs and 2) the share of the value of total output attributable to intermediate inputs remains constant over time.

Using the value for intermediate inputs reported in the survey data, I calculate a share of the value added (VASH) by the final inputs to final output. I do this by subtracting the value of the intermediate inputs (INT) from the value of total output (output price (p_s) multiplied by quantity produced (QP_s)), and then divide this difference by the same value of total output:

$$VASH_s = \frac{p_s QP_s - INT_s}{p_s QP_s}$$

and, using the value of $VASH_s$, I calculate a value-added output price (pva) as

$$pva_s = p_s \times VASH_s$$

where the value-added price represents the value of the output produced using the final inputs *net of* the value of any intermediate inputs used in the production process. For the sectors that reported no use of intermediate inputs, $pva_s = p_s$. Even though output price and total output in a sector may vary over time in the model, I do not recalculate the value of $VASH_s$ in each time period and instead use baseline values of $VASH_s$ that remain fixed over the study period. Fuel is used in the fishing sector and is modeled as an intermediate input acquired from the service sector in the local economy. As with intermediate inputs in other sectors, I assume that $VASH_{fish}$ is constant over time.

2.7.3 Factor Demands

Using (2.18), the profit-maximizing producer's quantity demanded for final inputs can be written as

$$f_{i,s,t} = \frac{pva_{s,t} QP_{s,t} \delta_{i,s}}{w_{i,t}} \tag{2.20}$$

where the factor demands used in the local economy include effective labor, capital, land, and final inputs. Capital and land are classified as nontradeable inputs, which means that the supply of these inputs is fixed at the household level. Labor is tradeable between households in the local economy, resulting in changes in the supply of effective labor due to changes in the wage paid to labor. According to the Ugandan Bureau of Statistics, the unemployment rate in Kalangala District was approximately 23% around the time of the survey (UBOS, 2017). I assume that the local labor supply is highly elastic, which is in line with previous studies (Taylor, Whitney, and Zhu, 2019). In Chapter 4, I test the sensitivity of my main results to changes in the elasticity of the labor supply. Final inputs are tradeable outside the local economy, which means that the price for these inputs is fixed over the study period.

I estimate the production functions in each of the sectors using logged values for output and factor demands. To preserve observations that reported zero values for some (but not all) of the variables used in the regressions, I replace logged values using an inverse hyperbolic sine function. This method permits retention of data for households who were producers but did not use one of the factors of production, or households who engaged in production but reported zero output, possibly due to theft or loss of harvest.

The fishing sector only employs effective labor and capital, with capital accounting for two-thirds of the value-added production in that sector for the non-stock inputs. Producers in the oil palm and other crops sectors reported no use of machinery or other capital assets in the production process. The high share of capital in livestock production corresponds to the value of the animal stock used in the production process. Land value-added shares are

Table 2.3: Estimates for Production Function Output Elasticities

Variables	Stat	Fishing	Oil Palm	Crops	Livestock	Retail	Services
Effective Labor	coef.	0.33***	0.41***	0.14***	0.58***	0.14*	0.14***
	s.e.	(0.01)	(0.172)	(0.051)	(0.073)	(0.081)	(0.054)
Capital	coef.	0.67***	–	–	0.23***	0.17***	0.149*
	s.e.	(0.01)	–	–	(0.056)	(0.07)	(0.08)
Land	coef.	–	0.54***	0.77***	0.07***	–	–
	s.e.	–	(0.168)	0.059	(0.025)	–	–
Inputs	coef.	–	0.05*	0.1***	0.12**	0.68***	0.72***
	s.e.	–	(0.031)	(0.03)	(0.049)	(0.1)	(0.07)
Shift Param.	coef.	1.67	2.5	1.51***	7.89***	7.0***	8.0***
	s.e.	(1.172)	(1.901)	(0.35)	(0.742)	(1.08)	(0.89)
Observations		84	98	129	265	114	129

Notes: Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: Original Data

larger for other crops than for oil palm, reflecting the relative importance of other inputs, including labor, in the production of oil palm. Inputs for both types of businesses contribute the majority of value-added to the production process.

Expenditure shares are estimated using a seemingly unrelated regression approach in *Stata*, which accounts for potential correlation in the error terms across equations. This means that for each household, a set of equations is estimated jointly, with one equation for each consumption category shown in Table 2.4. The equations are constructed with the category expenditure as the dependent variable and total expenditures as the independent variable. Household expenditures reflect both market transactions as well as the market value of goods produced and consumed within the household.

Table 2.4: Household Expenditure Share Estimates

Household	Fish	Crops	Livestock	Retail	Services	Outside
Poor, Fishing	0.08***	0.28***	0.07***	0.21***	0.23***	0.12**
(n=14)	(0.023)	(0.052)	(0.022)	(0.043)	(0.032)	(0.049)
Nonpoor, Fishing	0.25***	0.12***	0.05***	0.18***	0.22***	0.18***
(n=70)	(0.054)	(0.014)	(0.009)	(0.024)	(0.034)	(0.035)
Poor, Nonfishing	0.07***	0.27***	0.09***	0.21***	0.21***	0.16***
(n=172)	(0.009)	(0.016)	(0.009)	(0.014)	(0.012)	(0.018)
Nonpoor, Nonfishing	0.06***	0.17***	0.06***	0.24***	0.26***	0.21***
(n=255)	(0.006)	(0.009)	(0.004)	(0.012)	(0.012)	(0.015)
Total	0.08***	0.20***	0.07***	0.22***	0.24***	0.19***
(n=511)	0.007	0.008	0.004	0.008	0.008	0.011

Notes: Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: Original Data

On average, I estimate that households allocate just under 10% of their budget on fish. Nonpoor fishing households are the exception, with a quarter of total expenditures going to fish consumption. Crops account for one-fifth of household consumption on average. Poor households consume a larger share of crops relative to nonpoor households, possibly reflecting the role of subsistence agriculture in household consumption. Livestock only accounts for 7% of household consumption. Retail and service businesses account for just under half of total consumption, with nonpoor-nonfishing households consuming above the average amount. Nonpoor households consume more outside purchases relative to poor households.

2.8 Parameter Values for The Epi Component

The parameters in the Epi component are assigned values following a process centered around identifying an interval for the basic reproductive number, R_0, that is grounded in previous research and is relevant for Schisto.

The expression for R_0 is

$$R_0 = \frac{\beta \chi \sum_{h=1}^{H} g_h \tau_h^E \tau_h^C \epsilon_h^E \epsilon_h^C}{\mu \gamma} \tag{2.12}$$

with time subscripts suppressed. For the main analysis, I assume that χ is equal to and varies over time with the exposure rate parameter, β. This assumption is reasonable for diseases like Schisto, since it is likely that contamination occurs via the same behaviors that lead to exposure to the parasite (Mari et al., 2017; Woolhouse et al., 1998).

In order to establish an interval for R_0, I first assume that

$$\epsilon_h^E = \epsilon_h^C = 1 \qquad \text{and} \qquad \tau_h^E = \tau_h^C = 1$$

which states that each household type has the same amount of time and risk for both exposure to and contamination with the disease. The purpose of this step is to construct an appropriate interval for R_0 that is comparable to previous studies with populations that are assumed to be homogeneous with respect to exposure risk and time. Sokolow *et al.* (2015) identifies parameter values based on an expected R_0 between 1 and 7, while Garchitorena *et al.* (2017) assumes an endemic equilibrium R_0 of 3. Halstead *et al.* (2018) identifies a maximum R_0 of 3.6 in their empirical study of the relationship between agrochemicals and densities of schistome-infected snails. Since each of these studies implicitly assumes that the population is homogeneous with respect the risk of exposure and contamination, it is appropriate to construct the interval for the R_0 in this study such that the maximum value for a homogeneous population is comparable to those used in previous studies.

The expression for R_0 simplifies to

$$R_0 = \frac{\beta^2}{\mu\gamma} \tag{2.21}$$

after invoking the assumption that each household type has the same amount of exposure (and contamination) time and risk. Following Mari et al. (2017) and Garchitorena et al., 2017, I assign the value of $\mu = 1.7 \times 10^{-2}$. As discussed above, I model the parameters β and γ are both functions of aggregate output Z, which can vary over time. I establish minimum and maximum values for these parameters in line with values from previous studies, with $\beta_{min} = 5.8 \times 10^{-4}$ and $\beta_{max} = 5.8 \times 10^{-3}$ and $\gamma_{min} = 5.5 \times 10^{-4}$ and $\gamma_{max} = 5.5 \times 10^{-3}$ (Mari et al., 2017; Garchitorena et al., 2017). I define values for the median and slope parameters for β and γ using country-level data from the World Bank (World Bank, 2022) (see Appendix 2.A).

I use the values of β_{max} and γ_{min} to calculate the maximum value of R_0. I choose these values because I assume that high rates of endemicity of the disease correspond to high rates of exposure to the disease and low rates of mortality of the parasite in the human population. Based on these parameter values, I calculate a maximum value of $R_0 = 3.6$. This value is the same value found in Halstead et al. (2018) and is in line with values from related studies noted above. It is worth emphasizing that this maximum value is based on a population with homogeneous risk of exposure and contamination. In the presence of heterogeneous risk of exposure and contamination across subpopulation groups, the observed R_0 may exceed this maximum value (Mari et al., 2017).

2.8.1 Exposure-Contamination Risk Parameters

The exposure and contamination risk parameters represent the risk of exposure to or contamination of the environment with the parasite that causes the disease that household h faces relative to other households. This risk may stem from differences in socioeconomic status, occupation, location, or ethnicity (Moira et al., 2007).

I assume that $\epsilon_h^C = \epsilon_h^E$ for each household and denote the Exposure-Contamination (E-C) risk parameter for each household as ϵ_h. This assumption states that for a given household, the risk of exposure to the disease is equal to the risk of contamination. As noted before, such an assumption is reasonable for diseases like Schisto, since it is likely that contamination occurs via the same behaviors that lead to exposure to the parasite (Mari et al., 2017; Woolhouse et al., 1998).

I identify values for ϵ_h using the survey data described above. Specifically, I combine data on household expenditures and data related to behaviors that are known to correlate with the disease: water collection and access to WASH facilities. Expenditure data is a proxy for *private* investment by the household in disease treatment and prevention. Data on water collection was collected in the individual roster of the survey and are aggregated at the household level. In the survey module on household assets, there are two questions related to access to clean WASH facilities. [4] For each source, Table 2.5 lists the question or section identifier found in the survey, the question content, and (if applicable) the recall window.

To calculate values of ϵ_h, I begin by producing raw averages at the household level for each of the four measures identified in Table 2.5. For each measure, a larger value correlates with an increased risk of exposure and contamination. Responses to the questions about main water source (WS) and access to toilet facilities (TF) were originally reported as single choices from a list of options. For these questions, I converted the data to a binary variable by reclassifying the choices as improved (0) or unimproved (1). I use values for water collection reported in the individual roster to create a measure of daily per capita water collection time for the household. I calculate an inverse measure of per capita household expenditures by

[4] Domestic production—which includes activities like water collection, cooking, cleaning, and child-rearing—is not identified as a productive activity in the LEWIE component for this study since, as in similar data collection efforts, domestic time use data were not gathered. As domestic production represents an additional transmission pathway for the disease in the local economy, future studies that adopt the modeling approach used in this study could begin to rectify this omission with a survey design that recognizes these as value-adding activities for the local economy.

Table 2.5: Survey Data for Calculation of the E-C Parameter Values

Question Identifier	Question Content	Recall Window
TS001	Time spent collecting water	Hours in a typical day
HS003	Main water source (Household)	N/A
HS004	Access to Toilet Facilities	N/A
Household Expenditure Section		Various; Synchronized

Source: Original Data

dividing per capita household expenditure aggregate values into 1. Raw averages exclude outliers that are defined at the 97$^{\text{th}}$ percentile based on expenditures.

Table 2.6: Summary Statistics and Estimated E-C measures

Household Type	Pop Share (%)	Water Collection	WS	TF	Expenditures (inverse)	ϵ_h
		WC	WS	TF	exp	
Poor, Fish	2.7	1.59	33.3%	16.7%	4.4×10^{-4}	1.064
		1.038	0.979	0.741	1.486	
Nonpoor, Fish	13.6	1.82	20.5%	20.5%	1.2×10^{-4}	0.876
		0.951	0.823	0.912	0.410	
Poor, Nonfish	33.7	2.35	36.8%	22.4%	4.5×10^{-4}	1.232
		1.122	1.081	0.996	1.536	
Nonpoor, Nonfish	49.9	1.63	33.0%	24.1%	1.4×10^{-4}	0.874
		0.851	0.971	1.072	0.477	

Notes: The E-C risk parameter for each household is shown in the rightmost column. For each household, raw averages for each measure are shown above the household's normalized value for that measure. Water Collection is measured in hours per day.
Source: Original Data.

For each of the four measures, I normalize the raw average for the household by dividing by the population-weighted mean. For example, the normalized value of water collection time (WC) for household h is calculated as

$$\epsilon_{WC,h} = \frac{WC_h}{\sum\limits_{\tilde{h}=1}^{H} g_{\tilde{h}} WC_{\tilde{h}}}$$

where the summation term in the denominator is over all households. Dividing by the mean produces a unit-free value, which allows for aggregation across measures with different units (e.g., hours per day and expenditures). I then calculate ϵ_h as

$$\epsilon_h = \frac{1}{4}\Big[\epsilon_{WC,h} + \epsilon_{WS,h} + \epsilon_{TF,h} + \epsilon_{exp,h}\Big]$$

which, being a simple average, means that I assume that each measure is of equal importance in determining the value of ϵ_h.

Overall, poor households reported spending more time than nonpoor households collecting water and using unimproved water supplies with greater frequency. Nonpoor fishing households reported a greater frequency of unimproved toilet facilities. Poor nonfishing households have the highest E-C risk parameter value at 1.232, which may reflect the impact of lower average expenditures for these households compared to poor fishing households. Both nonpoor household groups have approximately the same E-C risk parameter value, possibly reflecting tradeoffs between exposure to the disease via fishing and higher expenditures reported by fishing households.

2.8.2 Exposure Time

The addition of an explicit measure of exposure time, τ_h, to the disease dynamics is a key contribution I make to the current literature. The measure of exposure time represents two of the primary ways in which individuals are exposed to the disease–household production activities like water collection and fishing labor time. Having said that, only fishing labor time varies over the study period, as water collection time is fixed.

To calculate the baseline levels of exposure time for each household, I calculate a fixed value, which consists of the values for water collection time identified in Table 2.6, and a variable value, which consists of fishing labor time supplied by the household, converted to daily values. For fishing households, fishing labor time is approximately 80% of the household's baseline level of exposure time. The baseline value of τ_h is normalized to 1 for each household. I calculate exposure time for the household at time t as

$$\tau_{h,t} = \bar{\tau}_h + \frac{L_{h,fish,t}}{L_{h,fish,baseline}} \tag{2.22}$$

where $\bar{\tau}_h$ is the fixed value of exposure time. The variable component of exposure time is calculated by dividing the amount of fishing labor time supplied by household h by the baseline amount of fishing labor time supplied by household h. The value of $L_{h,fish,t}$ is solved for using the amount of effective labor supplied by the household to the fishing sector and the household's infection status. For nonfishing households, exposure time remains constant over time. For fishing households, exposure time may change as a result of changes in their labor allocation across sectors.

2.9 Parameter Values for the Bio Component

The state equation for the biological population component of the model is:

$$\dot{X} = X_t r_{fstock}(1 - \frac{X_t}{K_{lake}}) - HARV_t \ . \tag{2.17}$$

The first parameter value from Eq. (2.17) that I source from previous literature is r_{fstock}, the growth rate for the composite fish stock. I follow Kateregga and Sterner (2009), which utilized a biological population model for the composite fish stock in Lake Victoria, by assuming $r_{fstock} = 1.06$.

The value for the carrying capacity of the local fishing area, $K_{lake} = 20,139$ metric tons, is based on the assumption that the stock of fish are essentially distributed uniformly across the lake and estimated as follows. I source an estimate of the carrying capacity for the Ugandan portion of Lake Victoria, 492,000 metric tons (Kateregga and Sterner, 2009). I estimate the share of the fishing area for the local economy by calculating the Ugandan portion (45%) of Lake Victoria total surface area to be $0.45 \times 68.800\,\text{km}^2 = 30.960\,\text{km}^2$. Next, I estimate a fishing area around Bugala Island of $1267\,\text{km}^2$ (see Figure 2.4).[5]

I estimate the share of the Ugandan portion of the lake that is fished by the local economy to be

$$\frac{1267\,\text{km}^2}{30.960\,\text{km}^2} = 4.1\% \,.$$

I then multiply 4.1% by the estimate of 492,000 metric tons from Kateregga and Sterner (2009), obtaining a value of 20,139 metric tons for the carrying capacity of the local fishing area. The baseline value of $HARV$ is assigned using the output from the baseline solution process of the EBL model, described next.

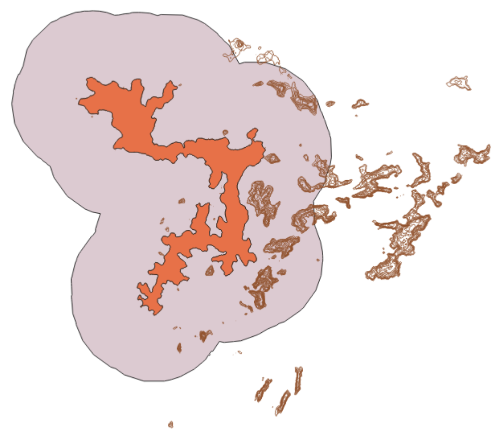


Figure 2.4: Fishing area around Bugala Island.

2.10 Constructing the EBL Model

There are a total of 360 equations that comprise the EBL model: 9 equations in the Epi component, 1 equation in the Bio component, and 350 equations in the LEWIE component, with a corresponding number of variables whose values are identified in the solution process (see Appendix 2.C for a complete list of model equations and corresponding variables). The objective of the process outlined in this section is to obtain baseline solutions for the

[5]The fishing area around Bugala Island was estimated by creating a polygon perimeter around the island with a distance of 10 km from the island shoreline, using *QGIS ver.* 3.22.14. The value of this distance was informed by conversations with local fisherman during my field visit in 2020.

EBL model such that equilibrium is reached within each component model and between component models. Absent any changes to parameter values in the EBL model, including those that result from a simulated policy shock, the EBL model will remain in equilibrium. The EBL model is solved as a mixed complementarity problem (MCP) using the *MCP* solver in General Algebraic Modeling System (*GAMS*) software *ver.* 24.1.3.

2.10.1 Drawn Parameter Values

The process of estimating parameter values using survey data produces point estimates with standard errors. Following previous studies, I could prepare the model for analysis using the point estimates for the exogenously determined parameters, which allows me to generate a single time path for each outcome (e.g., Gilliland, Sanchirico, and Taylor, 2019; Lindsay et al., 2020). However, since the point estimates likely differ from the true values of the parameters, I produce a more nuanced representation of the effects of the policy shocks by taking advantage of the estimated standard errors, which is an approach common to before-after studies that employ a LEWIE model (e.g., Taylor and Filipski, 2014b). Specifically, I produce 1,000 sets of baseline equilibrium values for the EBL model using 1,000 realizations of the baseline local economy, as described in the process below.

2.10.2 Preparing the LEWIE Component for Analysis

I assign 1,000 values for each of the exogenously determined parameters of the model (see Table 2.7) by sampling from a normal distribution with a mean equal to the point estimate and a variance equal to the square of the estimated standard error.

I assume a baseline value of 1 for output prices and factor prices, a common approach that allows for interpreting results as percentage changes in prices and wages relative to baseline (e.g., Taylor and Filipski, 2014a). I assume an elasticity of substitution between consumption goods of 3 for each household and a trade elasticity of 8 for the composite good, fish, which

Table 2.7: Exogenous Parameters with Sampling Used to Solve for Baseline Solutions for the LEWIE Component.

Identifier	Definition
$fshare(f, g, h, dr)$	Share of input factor f used in the production of output g by household h
$eshare(g, h, dr)$	Share of household h's total expenditures allocated to consumption of good g
$sav(h, dr)$	Savings by household h (share of total household income)
$trout(h, dr)$	Net transfers out by household h (share of total household income)
$expout(h, dr)$	Expenditures outside of the local economy by household h (share of total household income)

Notes: Relevant sets for each parameter, as are shown in parentheses in the table, are as follows: $f \rightarrow$ factor input; $g, gg \rightarrow$ produced good; $h \rightarrow$ household; $dr \rightarrow$ draw.

implies that imported fish are a close substitute for locally harvested fish. This assumption makes sense as imported fish are most likely come from within the region and thus are likely coming from the same source, Lake Victoria, as locally harvested fish. I use the survey data to calculation population shares for each household type, which enter into the model as the parameter $popsh(h)$.

Endogenously Determined Parameter Values and Solutions to the Model

The remaining parameter values are endogenous to the LEWIE component of the model and are obtained during the process of solving for the baseline values of the EBL model, which are chosen to match the conditions of the baseline economy as observed in the data. Using the sampled values and model assumptions described above, I calculate the values of the endogenous parameters and the solution values for the LEWIE component variables as identified in Table 2.9.

Table 2.8: Model Assumptions for Solving for Baseline Solutions for the LEWIE Component

Identifier	Assumption
$p(g) = 1$	Output prices are equal to 1
$r = 1$ $w = 1$	Factor wages for capital (r) and labor (w) are equal to 1
$tr\_elas(g) = 8$	Trade elasticity for good g is equal to 8; constant over time
$good\_elas(h) = 3$	Consumption elasticity for household h is equal to 3; constant over time
$p\_imp(g) = 1$	Import price of good g is equal to 1
$p\_comp(g) = 1$	Composite of domestic and import prices of good g is equal to 1

Notes: Relevant sets for each parameter, as are shown in parentheses in the table, are as follows: $f \rightarrow$ factor input; $g, gg \rightarrow$ produced good; $h \rightarrow$ household; $dr \rightarrow$ draw.

Table 2.9: Values, presented in order of calculation, that are either parameter values or initial guesses for obtaining baseline solutions for the LEWIE component.

Identifier	Description	Calculation
QC(g,h,dr)	Monetary value of the quantity of good g consumed by household h	$[\mathbf{HHINC}(\cdot) - sav(\cdot) - trout(\cdot) - expout(\cdot)] \times \frac{eshare(\cdot)}{p(\cdot)}$
ID(gg,g,h,dr)	Monetary value of the intermediate demand for good gg used in the production of final output g by household h	$\mathbf{QP}(\cdot) \times idsh(\cdot)$

Continued on next page

Table 2.9 – continued from previous page

Calculated Values	Description	Calculation
FD(g,f,h,dr)	Monetary value of the quantity demanded of input factor f in the production of good g by household h	$[\mathbf{QP}(\cdot) - \sum_{gg} \mathbf{ID}(\cdot)] \times fshare(\cdot)$
QVA(g,h,dr)	Monetary value of quantity of good g produced by household h	$\sum_f \mathbf{FD}(\cdot)$
$tfpshift(g,h,dr)$	Total Factor Productivity value for good g produced by household h	$\frac{\mathbf{QVA}(\cdot)}{\prod_f \mathbf{FD}(\cdot)^{fshare(\cdot)}}$
IMP(g,dr)	Imports of good g	$\frac{1-domsh(\cdot)}{domsh(\cdot)} \times \sum_g \mathbf{QP}(g,\cdot)$
$vash(g,h,dr)$	Final inputs' share of the total value of output g produced by household h	$\frac{\mathbf{QP}(\cdot) - \sum_{gg} \mathbf{ID}(\cdot)}{\mathbf{QP}(\cdot)}$
$endow(f,h,dr)$	Household h's endowment of factor f	For Land and Capital : $\sum_g \mathbf{FD}(\cdot)$ For Labor : $popsh(\cdot) \times \sum_{g,h} \mathbf{FD}(\cdot)$

Continued on next page

Table 2.9 – continued from previous page

Calculated Values	Description	Calculation
$delta(g, dr)$	Share parameter for the Armington function	$\frac{\mathbf{IMP(\cdot)}}{\sum_h \mathbf{QP(\cdot)}}^{tr\_elas(\cdot)} \times \left[\frac{p\_imp(\cdot)}{p(\cdot)} + \frac{\mathbf{IMP(\cdot)}}{\sum_h \mathbf{QP(\cdot)}}^{tr\_elas(\cdot)}\right]^{-1}$
TQP_COMP(g,dr)	Aggregate output of composite good g	$\mathbf{IMP(\cdot)} + \sum_h \mathbf{QP(\cdot)}$

Notes: Parameters are written in italic font. Variables are capitalized and written in bold font. Relevant sets for each parameter or variable are represented in parentheses as follows: $f \rightarrow$ factor input; $g, gg \rightarrow$ produced good; $h \rightarrow$ household; $dr \rightarrow$ draw.

2.10.3 Preparing the Epi Component for Analysis

In contrast to the LEWIE component, values for the variables I_h and Y in the Epi component are not sourced from survey data or model assumptions. I do not incorporate Schisto test results in the process of preparing the EBL model for analysis (although I do use summary values of infection rates from previous research to validate the predicted values of I_h). Instead, values for the variables I_h and Y are "free" variables that are solved for simultaneously along with values in the LEWIE component, which ensures that the EBL model is in equilibrium within and between component models. For equilibrium to be reached in the EBL model, it needs to be the case that baseline household infection rates are consistent with the levels of effective labor supplied by households to the local economy (i.e., Equation

(2.9) holds), and that baseline levels of exposure time and aggregate output observed in the local economy correspond to the same baseline levels of infection (i.e., Equation (2.10) holds). Because the Epi and LEWIE component variables are solved simultaneously, the baseline solution values for I_h and Y meet these conditions.

2.10.4 Preparing the Bio Component for Analysis

The baseline level of the fish stock is identified by assuming that the fish stock is at a steady state, which means that absent any changes to the values in the growth equation, the fish stock level does not change over time. With this assumption in place, the left side of Eq. (2.17) is equal to zero, and

$$X_{SS} r_{fstock}(1 - \frac{X_{SS}}{K_{lake}}) = HARV_{baseline} \tag{2.23}$$

where X_{SS} is the steady-state level of the fish stock and $HARV_{baseline}$ is the baseline level of harvest by the fishing sector of the local economy. Equation (2.23) states that the level of natural growth of the fish stock is equal to the level of harvest by the fishing sector.

The value of $HARV_{baseline}$, which is obtained by jointly solving the Epi and LEWIE components, can be used to solve for X_{SS}. Because I do not solve the Bio component simultaneously with the LEWIE and Epi components, one more adjustment is necessary. As observed in Eq. (2.19), the fish stock enters into the production function for the fishing sector as an input. However, the level of the fish stock is unknown when solving for $HARV_0$ in a process that requires the production function for the fishing sector. To address this, the level of the fish stock is set equal to 1 when solving for the equilibrium values of the LEWIE and Epi components. The corresponding production function for the fishing sector is

$$QP_{fish} = A_{Restr,fish} \prod_{j=1}^{J} f_{j,fish}^{\delta_j} 1^{\delta_{fstock}} \ . \tag{2.24}$$

where $A_{Restr,fish}$ is the fishing sector TFP shift parameter when $X = 1$. Since $X_{SS} \neq 1$, the value of $A_{Restr,fish}$ obtained by jointly solving the Epi and LEWIE components is *incorrect*. With X_{SS} obtained as described above, the correct value of the TFP shift parameter can be found as follows. Comparing Eq. (2.24) with the unrestricted equation (introduced above in section 2.7),

$$QP_{fish} = A_{fish} \prod_{j=1}^{J} f_{j,fish}^{\delta_j} X^{\delta_{fstock}} \tag{2.19}$$

the right sides of both equations can be set equal to each other, with

$$A_{Restr,fish} = A_{fish} X^{\delta_{fstock}}$$

obtained after canceling terms. The correct value of the TFP shift parameter for the fishing sector, A_{fish}, can therefore be found by dividing the restricted value of A_{Restr} obtained in the joint LEWIE-Epi solution process by the value of X_{SS} raised to the power of δ_{fstock}.

2.10.5 LEWIE Component: Baseline Results

The output for the LEWIE component obtained from the steps outlined above can be used to construct a balanced Social Accounting Matrix (SAM) for the local economy. The SAM for the local economy can more accurately be described as a meta-SAM, since it is an aggregation of SAMs that can be constructed for each of the representative households in the economy. A SAM is a useful tool for visualizing the flow of payments between agents in the local economy as well as payments sent to and received from outside the local economy (Taylor and Filipski, 2014a).

The bold cells in Table 2.10 indicate the types of information obtained from the solution process described above. Payments flow from columns to rows. No cells along the diagonal are in bold because an account does not pay itself. Households participate in Activities (or

Table 2.10: A Stylized Meta-SAM for the LEWIE Component

Accounts	Activities	Commodities	Factors of Production	Households	Rest Of World
Activities	A1	**B1**	C1	D1	E1
Commodities	**A2**	B2	C2	**D2**	**E2**
Factors of Production	**A3**	B3	C3	D3	E3
Households	A4	B4	**C4**	D4	**E4**
Rest Of World	A5	**B5**	C5	**D5**	E5

Sectors) in which they employ Factors of Production (and use Commodities as intermediate inputs) in order to produce Commodities. The cell $B1$ can be read as payments from Commodities to Activities and indicates the value of final output that is produced by households in each sector. The accounting identity that states that the value of output is equal to the value of all inputs (intermediate and final) can also be written as $B1 = A2 + A3$. Payments between the local economy and the Rest of World can be recorded as either imports, which are represented in cells $B5$ and $D5$, or exports, which are represented in cells $E2$ and $E4$. Household expenditures are recorded in $D2$, and household income earned from their factors of production, including labor, are recorded in $C4$.

Baseline Characteristics

Table 2.11 shows the point estimates for the baseline levels of total factor demands and the shares for each sector. Approximately 15% of effective labor employed in the local economy is demanded in the fishing sector. Oil palm producers demand almost half of the total effective labor. The majority of the capital stock in the local economy is allocated to the fishing sector.

Table 2.12 shows the point estimates for the baseline levels of effective labor demanded by

Table 2.11: Estimates of Factor Demand Levels and Shares by Sector

Variables	Value*	Sector Share (%)					
		Fishing	Oil Palm	Food Crops	Livestock	Retail	Services
Labor	35,526	15.1	46.2	6.4	22.2	4.0	6.0
Capital	17,403	59.2	0.0	0.0	17.8	10.1	12.9
Land	35,169	0.0	60.5	36.8	2.8	0.0	0.0
Inputs	23,709	0.0	8.7	6.9	7.0	29.1	48.3

Notes: Values given in millions of Ugandan shillings.
Source: Original data.

Table 2.12: Estimates of Household Demand For Effective Labor and Shares by Sector

Households	Value*	Sector Share (%)					
		Fishing	Oil Palm	Food Crops	Livestock	Retail	Services
Poor, Fish	6,960	60.3	22.3	3.4	9.4	0.0	4.7
Nonpoor, Fish	2,372	50.0	30.7	3.2	9.7	2.0	4.4
Poor, Nonfish	7,184	0.0	48.5	13.1	35.1	1.8	1.5
Nonpoor, Nonfish	19,011	0.0	56.0	5.4	23.6	6.6	8.4

Notes: *Values given in millions of Ugandan shillings.
Source: Original data.

each household across sectors. Poor fishing households allocate 60% of their labor to the fishing sector, while nonpoor fishing households allocate half of their labor to the fishing sector and the majority of their remaining labor to oil palm production. Nonfishing households allocate approximately half of their labor to oil palm, with livestock production accounting for approximately one-third of labor coming from nonfishing households.

Table 2.13: Sector Contributions to Aggregate Output by Household Type

Household	Value of Output	Sector Share (%)					
		Fishing	Oil Palm	Food Crops	Livestock	Retail	Service
Poor, Fishing	9,568	52.9	13.2	6.1	8.9	3.3	15.7
Nonpoor, Fishing	28,541	44.6	18.4	5.9	7.4	8.8	14.9
Poor, Nonfishing	24,756	0.0	34.1	28.2	22.5	9.2	6.0
Nonpoor, Nonfishing	86,026	0.0	30.0	8.8	10.0	25.5	25.8
Aggregate	148,891	11.3	28.2	11.8	9.7	17.9	21.3

Notes: Value of output given in millions of Ugandan shillings.
Source: Original data.

Table 2.13 shows the relative contributions from each sector to aggregate output in the local economy based on point estimate values of output. The fishing sector accounts for 11.3% of aggregate output and businesses account for almost 40% of aggregate output. The oil palm sector generates almost one-third of all output.

2.10.6 Epi Component: Baseline Results

The baseline levels of the Epi parameters and state variables (see Table 2.14) are identified in the joint solution process described above.

Table 2.14: Baseline Results for the Epi Component

(a) Baseline Infection Rates

Household	Infection Rate
Poor, Fishing	57.1%
Nonpoor, Fishing	52.3%
Poor, Nonfishing	60.6%
Nonpoor, Nonfishing	52.2%
Snails	15.0%

Source: Original data.

(b) Parameter Values

Parameter	Baseline Value
R_0	2.76
β_0	5.42×10^{-3}
γ_0	7.1×10^{-4}

According to the results obtained using the point estimates for parameter values, the baseline population-weighted average infection rate for the model is 55.1%. This result is in line with previous studies identifying prevalence of the disease in Kalangala District Standley et al., 2011. Poor households have a higher infection rate than nonpoor households, reflecting the impact of income on access to treatment measures for the disease. The multiple sources of exposure time are accounted for in the model and are reflected in the variation in household infection rates. The baseline R_0 value of 2.76 is in line with previous empirical studies identifying basic reproductive numbers for Schisto (Halstead et al., 2018).

2.10.7 Bio Component: Baseline Results

To identify the value of $HARV_0$, I convert the baseline value of total harvest identified from the output of the solution values of the LEWIE component of the model into kilograms by multiplying this amount by a composite price of 5,159 Ugandan shillings per kilogram, yielding a total baseline harvest of 4,750 metric tons. This harvest-share weighted composite price was calculated using historical price and harvest data shared with me by the Kalangala District office of the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF).

Using the values for r_{fstock}, K_{Lake}, and $HARV_0$, I set Eq. (2.17) equal to zero and solve for X_0. I find two positive values from the resulting quadratic equation: $X_0 = 6,730$ and $X_0 = 13,408$. The latter value implies that the baseline stock of fish exceeds the maximum sustainable yield of $^{K_{Lake}}/_2 = 10,070$ metric tons that can be identified from the logistic growth function, which is inconsistent with the well-documented state of overfishing that characterizes the Lake Victory fishery (Witte et al., 1992; Balirwa et al., 2003; Kolding et al., 2014; Secretariat, 2016). Instead, I use the value of $X_0 = 6,730$, which implies a baseline fraction of stock size to carrying capacity of 33% that is in line with the value of 36% used in previous studies with open access fisheries (Manning, Taylor, and Wilen, 2018; Gilliland, Sanchirico, and Taylor, 2019).

2.11 Solving the Model with Policy Shocks

With the EBL model now in equilibrium within and between component models, I simulate different types of policy shocks. Each policy shock is introduced by changing values for one of the parameters in the model. It is possible to study a wide variety of policies using this type of modeling. For example, prior literature has examined the impact of cash transfers to one or more representative households in the model, by increasing the income of the household above baseline values (Gilliland, Sanchirico, and Taylor, 2019; Taylor, Filipski, et al., 2016) and the impact of policy-based investments in targeted sectors, such as agricultural sectors, by increasing the amount of capital (Lindsay et al., 2020) or land (Taylor, Whitney, and Zhu, 2019) endowed to producer households above the baseline levels.

I consider both one-time and recurring shocks to the model by analyzing the model over a 10-year period in annual time steps. The static nature of the LEWIE component means that the local economy reaches equilibrium every year. The differential equation for the Bio component is treated as a step equation, for which the "step forward" is in annual increments. The solutions for the LEWIE component for each year include values for fishing labor time for each household, aggregate output, and output in the fishing sector, which then enter into the equations for the Epi and Bio components.

Annual time steps in this type of modeling are common for two reasons. First, an annual time step allows for the simulated policy shocks and related impacts to manifest in the economy. Second, the transition process of the state variable in the dynamic model, such as fish stocks, is often stated in annual terms because of the nature of the growth process of the biomass (Manning, Taylor, and Wilen, 2018; Gilliland, Sanchirico, and Taylor, 2019; Lindsay et al., 2020). This means that for year t, the solutions for the LEWIE component are found after adjusting the fishing sector's intermediate demand for fuel (which depends on the size of the fish stock in year t). The size of the fish stock in the next year can be calculated using the step-equation form of Eq. (2.17), which includes the total harvest from year t, converted to kilograms.

For the Epi component of the model, I assume that the disease dynamics evolve at a faster pace than the relatively slower dynamics of the local economy or population of the composite fish stock. Consequently, equilibrium in the Epi component can respond to changes in the LEWIE and Bio components, while adjustment in the Epi component occurs more quickly. The fast-slow dynamics approach here follows previous research with coupled models where one state variable evolves at a much shorter timescale than the other(s) (e.g., Rashkov et al., 2019).

With this assumption in place, the values for I_h and Y are at their steady-state (SS) levels, and Eqs. (2.10) and (2.11) enter into the model for year t as

$$\gamma I_{h,SS} = \beta \tau_h^E \epsilon_h^E Y(1 - I_{h,SS}) \tag{2.25}$$

$$\mu Y_{SS} = \chi(1 - Y_{SS}) \sum_{h=1}^{H} g_h \tau_h^C \epsilon_h^C I_{h,SS} \tag{2.26}$$

after setting $\dot{I}_h = 0$ and $\dot{Y} = 0$ and rearranging terms. The values of $I_{h,SS}$ and Y_{SS} for year t are solved for jointly with the values for the LEWIE component.

The value of R_0 for year t indicates which of the two equilibria for the Epi component is stable in year t. Whenever $R_0 > 1$, which is the case for the baseline conditions for Kalangala District and elsewhere where Schisto is prevalent, the EE is stable and the DFE is not feasible, even if exogenous shocks such as MDA programs are successful in temporarily reducing prevalence of—or even temporarily eradicating—the disease in the human population. In the next chapter, I discuss results from simulations using three types of policy shocks in order to understand the potential for economic policy to affect the value of R_0 for Schisto and thus whether the disease dynamics are trending toward disease endemicity or a disease-free environment.

Bibliography

Armington, Paul S. (1969). "A Theory of Demand for Products Distinguished by Place of Production (Une théorie de la demande de produits différenciés d'après leur origine) (Una teoría de la demanda de productos distinguiéndolos según el lugar de producción)". In: *Staff Papers (International Monetary Fund)* 16.1, pp. 159–178. ISSN: 00208027. URL: http://www.jstor.org/stable/3866403.

Audibert, Martine and Jean-Francois Etard (1998). "Impact of Schistosomiasis on Rice Output and Farm Inputs in Mali". In: *Journal of African Economies* 7.2, pp. 185–207. URL: https://EconPapers.repec.org/RePEc:oup:jafrec:v:7:y:1998:i:2:p:185-207.

– (2003). "Productive Benefits after Investment in Health in Mali". In: *Economic Development and Cultural Change* 51.3, pp. 769–82. URL: https://EconPapers.repec.org/RePEc:ucp:ecdecc:y:2003:v:51:i:3:p:769-82.

Balirwa, John S., Colin A. Chapman, Lauren J. Chapman, Ian G. Cowx, Kim Geheb, Les Kaufman, Rosemary H. Lowe-McConnell, Ole Seehausen, Jan H. Wanink, Robin L. Welcomme, and Frans Witte (Aug. 2003). "Biodiversity and Fishery Sustainability in the Lake Victoria Basin: An Unexpected Marriage?" In: *BioScience* 53.8, pp. 703–715. ISSN: 0006-3568. DOI: 10.1641/0006-3568(2003)053[0703:BAFSIT]2.0.CO;2. eprint: https://academic.oup.com/bioscience/article-pdf/53/8/703/26894589/53-8-703.pdf. URL: https://doi.org/10.1641/0006-3568(2003)053[0703:BAFSIT]2.0.CO;2.

Bank, World (2016). *The Uganda Poverty Assessment Report 2016 - World Bank*. URL: https://pubdocs.worldbank.org/en/381951474255092375/pdf/Uganda-Poverty-Assessment-Report-2016.pdf.

Barbosa, F. S. and D. P. Periera da Costa (1981). "Incapacitating Effects of Schistosomiasis Mansoni on the Productivity of Sugar-cane Cutters in Northeastern Brazil". In: *American Journal of Epidemiology* 114.1, pp. 102–111. ISSN: 0002-9262. DOI: 10.1093/oxfordjournals.aje.a113156. eprint: http://oup.prod.sis.lan/aje/article-pdf/114/1/102/226727/114-1-102.pdf. URL: https://doi.org/10.1093/oxfordjournals.aje.a113156.

Bonds, Matthew H., Donald C. Keenan, Pejman Rohani, and Jeffrey D. Sachs (2010). "Poverty Trap Formed by the Ecology of Infectious Diseases". In: *Proceedings of the Royal Society B: Biological Sciences* 277.1685, pp. 1185–1192. DOI: 10.1098/rspb.2009.1778. eprint: https://royalsocietypublishing.org/doi/pdf/10.1098/rspb.2009.1778. URL: https://royalsocietypublishing.org/doi/abs/10.1098/rspb.2009.1778.

Castonguay, François M., Susanne H. Sokolow, Giulio A. De Leo, and James N. Sanchirico

(2020). "Cost-Effectiveness of Combining Drug and Environmental Treatments for Environmentally Transmitted Diseases". In: *Proceedings of the Royal Society B: Biological Sciences* 287.1933, p. 20200966. DOI: 10.1098/rspb.2020.0966.

Diekmann, O., J. A. P. Heesterbeek, and M. G. Roberts (2009). "The Construction of Next-Generation Matrices for Compartmental Epidemic Models". In: *Journal of The Royal Society Interface* 7.47, pp. 873–885. DOI: 10.1098/rsif.2009.0386.

Downing, Andrea S., Nika Galic, Kees P. C. Goudswaard, Egbert H. van Nes, Marten Scheffer, Frans Witte, and Wolf M. Mooij (Oct. 2013). "Was Lates Late? A Null Model for the Nile Perch Boom in Lake Victoria". In: *PLOS ONE* 8.10, pp. 1–9. DOI: 10.1371/journal.pone.0076847. URL: https://doi.org/10.1371/journal.pone.0076847.

El Aferni, Ahmed, Moez Guettari, and Tahar Tajouri (Oct. 2020). "Mathematical Model of Boltzmann's Sigmoidal Equation Applicable to the Spreading of the Coronavirus (Covid-19) Waves". In: *Environmental Science and Pollution Research* 28.30, pp. 40400–40408. ISSN: 1614-7499. DOI: 10.1007/s11356-020-11188-y. URL: http://dx.doi.org/10.1007/s11356-020-11188-y.

Filipski, Mateusz and Ben Belton (Oct. 2018). "Give a Man a Fishpond: Modeling the Impacts of Aquaculture in the Rural Economy". In: *World Development* 110, pp. 205–223. DOI: 10.1016/j.worlddev.2018.05.023. URL: https://doi.org/10.1016/j.worlddev.2018.05.023.

Fiorella, Kathryn J., Erin M. Milner, Charles R. Salmen, Matthew D. Hickey, Dan O. Omollo, Abdi Odhiambo, Brian Mattah, Elizabeth A. Bukusi, Lia C. H. Fernald, and Justin S. Brashares (2017). "Human Health Alters the Sustainability of Fishing Practices in East Africa". In: *Proceedings of the National Academy of Sciences* 114.16, pp. 4171–4176. ISSN: 0027-8424. DOI: 10.1073/pnas.1613260114. eprint: https://www.pnas.org/content/114/16/4171.full.pdf. URL: https://www.pnas.org/content/114/16/4171.

Garchitorena, A., S. H. Sokolow, B. Roche, C. N. Ngonghala, M. Jocque, A. Lund, M. Barry, E. A. Mordecai, G. C. Daily, J. H. Jones, J. R. Andrews, E. Bendavid, S. P. Luby, A. D. LaBeaud, K. Seetah, J. F. Guégan, M. H. Bonds, and G. A. De Leo (2017). "Disease Ecology, Health and the Environment: A Framework to Account for Ecological and Socio-economic Drivers in the Control of Neglected Tropical Diseases". In: *Philosophical Transactions of the Royal Society of London B: Biological Sciences* 372.1722. ISSN: 0962-8436. DOI: 10.1098/rstb.2016.0128. eprint: http://rstb.royalsocietypublishing.org/content/372/1722/20160128.full.pdf. URL: http://rstb.royalsocietypublishing.org/content/372/1722/20160128.

Gilliland, Ted E., James N. Sanchirico, and J. Edward Taylor (2019). "An Integrated Bioeconomic Local Economy-wide Assessment of the Environmental Impacts of Poverty Programs". In: *Proceedings of the National Academy of Sciences* 116.14, pp. 6737–6742. DOI: 10.1073/pnas.1816093116. eprint: https://www.pnas.org/content/116/14/6737.full.pdf. URL: https://www.pnas.org/content/116/14/6737.

Gray, Darren J., Allen G. Ross, Yue-Sheng Li, McManus, and Donald P. (May 2011). "Diagnosis and Management of Schistosomiasis". In: *BMJ* 342. 21586478[pmid], pp. d2651–d2651. ISSN: 1756-1833. DOI: 10.1136/bmj.d2651. URL: https://www.ncbi.nlm.nih.gov/pubmed/21586478.

Halstead, Neal T., Christopher M. Hoover, Arathi Arakala, David J. Civitello, Giulio A. De

Leo, Manoj Gambhir, Steve A. Johnson, Nicolas Jouanard, Kristin A. Loerns, Taegan A. Mcmahon, and et al. (2018). "Agrochemicals Increase Risk of Human Schistosomiasis by Supporting Higher Densities of Intermediate Hosts". In: *Nature Communications* 9.1. DOI: 10.1038/s41467-018-03189-w.

Kamel, M.I., Y.A. Moustafa, N. Foda, S. Khashab, M. Moemen, and R.M. Abo El Naga (2002). "Impact of Schistosomiasis on Quality of Life and Productivity of Workers". In: *Eastern Mediterranean Health Journal* 8.2-3, pp. 354–362. URL: http://www.who.int/iris/handle/10665/119174.

Kateregga, Eseza and Thomas Sterner (2009). "Lake Victoria Fish Stocks and the Effects of Water Hyacinth". In: *The Journal of Environment & Development* 18.1, pp. 62–78. DOI: 10.1177/1070496508329467. URL: https://doi.org/10.1177/1070496508329467.

King, Charles H., Robert F. Sturrock, H. Curtis Kariuki, and Joseph Hamburger (Dec. 2006). "Transmission control for schistosomiasis – why it matters now". In: *Trends in Parasitology* 22.12, pp. 575–582. ISSN: 1471-4922. DOI: 10.1016/j.pt.2006.09.006. URL: http://dx.doi.org/10.1016/j.pt.2006.09.006.

Kolding, Jeppe, Medard Modesta, Oliva Mkumbo, and Paul van Zweiten (2014). *Inland Fisheries Evolution and Management: Case Studies from Four Continents*. Tech. rep. Food and Agriculture Organization.

Lindsay, Amanda R., James N. Sanchirico, Ted E. Gilliland, Rohani Ambo-Rappe, J. Edward Taylor, Nils C. Krueck, and Peter J. Mumby (2020). "Evaluating Sustainable Development Policies in Rural Coastal Economies". In: *Proceedings of the National Academy of Sciences* 117.52, pp. 33170–33176. ISSN: 0027-8424. DOI: 10.1073/pnas.2017835117. URL: https://www.pnas.org/content/117/52/33170.

Lofgren, Hans, Rebecca Lee Harris, and Sherman Robinson (Jan. 2002). *A Standard Computable General Equilibrium (CGE) Model in GAMS*. en. Intl Food Policy Res Inst.

Manning, Dale T., J. Edward Taylor, and James E. Wilen (Jan. 2018). "General Equilibrium Tragedy of the Commons". In: *Environmental and Resource Economics* 69.1, pp. 75–101. ISSN: 1573-1502. DOI: 10.1007/s10640-016-0066-7. URL: https://doi.org/10.1007/s10640-016-0066-7.

Mari, Lorenzo, Manuela Ciddio, Renato Casagrandi, Javier Perez-Saez, Enrico Bertuzzo, Andrea Rinaldo, Susanne H. Sokolow, Giulio A. De Leo, and Marino Gatto (Nov. 2017). "Heterogeneity in Schistosomiasis Transmission Dynamics". en. In: *Journal of Theoretical Biology* 432, pp. 87–99. ISSN: 00225193. DOI: 10.1016/j.jtbi.2017.08.015. URL: https://linkinghub.elsevier.com/retrieve/pii/S0022519317303818 (visited on 08/24/2021).

Moira, Angela Pinot De, Anthony J. C. Fulford, Narcis B. Kabatereine, Francis Kazibwe, John H. Ouma, David W. Dunne, and Mark Booth (2007). "Microgeographical and Tribal Variations in Water Contact and Schistosoma mansoni Exposure Within a Ugandan Fishing Community". In: *Tropical Medicine & International Health* 12.6, pp. 724–735. DOI: 10.1111/j.1365-3156.2007.01842.x.

Rashkov, Peter, Ezio Venturino, Maira Aguiar, Nico Stollenwerk, and Bob W. Kooi (2019). "On the Role of Vector Modeling in a Minimalistic Epidemic Model". In: *Mathematical Biosciences and Engineering* 16.5, pp. 4314–4338. DOI: 10.3934/mbe.2019215.

Secretariat, Lake Victoria Fisheries Organization (LVFO) (2016). *Fisheries Management Plan III (FMP III) for Lake Victoria Fisheries 2016-2020*. Tech. rep. Lake Victoria Fisheries Organization.

Ssemmanda, R. and M. Opige (2019). *An Assessment of the Impacts of Oil Palm in Kalangala and Buvuma: Lessons Learned and Recommendations for Future Developments.* Tech. rep. URL: https://www.tropenbos.org/resources/publications/an+assessment+of+the+impacts+of+oil+palm+in+kalangala+and+buvuma.

Standley, Claire J., Moses Adriko, Fred Besigye, Narcis B. Kabatereine, and Russell J. Stothard (2011). "Confirmed Local Endemicity and Putative High Transmission of *Schistosoma mansoni* in the Sesse Islands, Lake Victoria, Uganda". In: *Parasites & Vectors* 4.1, p. 29. DOI: 10.1186/1756-3305-4-29.

Taylor, J. Edward and Mateusz J. Filipski, eds. (2014a). *Beyond Experiments in Development Economics: Local Economy-Wide Impact Evaluation.* Oxford: Oxford University Press.

– (2014b). "Evaluating the Impact of Global Food Price Shocks in Rural Guatemala". In: *Beyond Experiments in Development Economics: Local Economy-Wide Impact Evaluation.* Oxford University Press, pp. 166–180.

Taylor, J. Edward, Mateusz J. Filipski, Mohamad Alloush, Anubhab Gupta, Ruben Irvin Rojas Valdes, and Ernesto Gonzalez-Estrada (June 2016). "Economic Impact of Refugees". en. In: *Proc Natl Acad Sci U S A* 113.27, pp. 7449–7453.

Taylor, J. Edward, Edward Whitney, and Heng Zhu (Oct. 2019). "Local-Economy Impacts of Cash Crop Promotion". In: *Food and Agricultural Organization, United Nations* 40 IFAD Research Series, pp. 1–34. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3465509.

UBOS, Uganda Bureau of Statistics (2017). *The National Population and Housing Census 2014 – Area Specific Profile Series.* Tech. rep.

Witte, Frans, Tijs Goldschmidt, Jan Wanink, Martien van Oijen, Kees Goudswaard, Els Witte-Maas, and Niels Bouton (May 1992). "The Destruction of an Endemic Species Flock: Quantitative Data on the Decline of the Haplochromine Cichlids of Lake Victoria". In: *Environmental Biology of Fishes* 34.1, pp. 1–28. ISSN: 1573-5133. DOI: 10.1007/BF00004782. URL: https://doi.org/10.1007/BF00004782.

Woolhouse, M. E. J., J.-F. Etard, K. Dietz, P. D. Ndhlovu, and S. K. Chandiwana (1998). "Heterogeneities in Schistosome Transmission Dynamics and Control". In: *Parasitology* 117.5, pp. 475–482. DOI: 10.1017/s003118209800331x.

World Bank (2021). *Banking on Protected Areas: Promoting Sustainable Protected Area Tourism to Benefit Local Economies.* URL: http://hdl.handle.net/10986/35737.

– (2022). *GDP, PPP (2017).* Data retrieved from World Development Indicators. URL: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD.

World Health Organization (2022). *WHO Guideline on Control and Elimination of Human Schistosomiasis.* World Health Organization.

2.A Assigning Slope and Median Parameter Values for β and γ

Equations (2.14) and (2.16) in section 2.3 are used to determine the relative weights for the assigned minimum and maximum values of the exposure rate, β, and mortality rate of the parasite in the human host, γ, respectively:

$$\phi_\beta(Z) = \frac{1}{1 + \exp\left(\frac{Z - Z_{med}}{Z_{slope}}\right)} \tag{2.14}$$

$$\phi_\gamma(Z) = \frac{1}{1 + \exp\left(\frac{-(Z - Z_{med})}{Z_{slope}}\right)} \tag{2.16}$$

I assign time-invariant values for the median and slope parameters for β and γ in this function using per-capita GDP for each country in 2017 as follows (World Bank, 2022). I convert each country value to Ugandan shillings (UGX) using the exchange rate of 3,600 UGX to 1 USD and convert to logged values. I calculate a scaling factor by dividing the baseline value of aggregate output Z, converted to per capita, by Uganda's per capita GDP. I add the logged value of the scale factor to thelogged value for each country, producing a log-normal distribution of GDP values, scaled to the local economy.

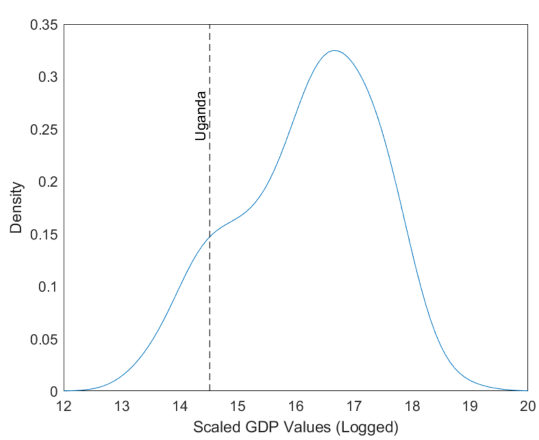


Figure A.1: Distribution of GDP values.

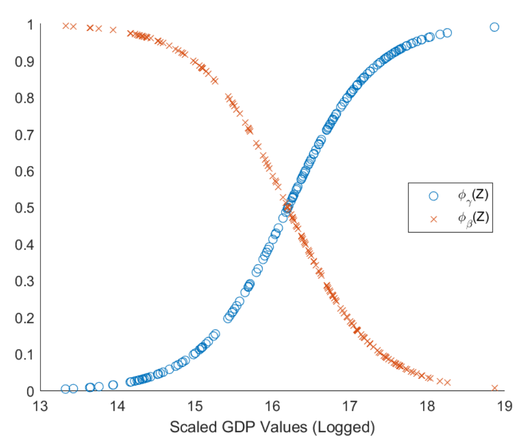


Figure A.2: Scatter plots of $\phi_\gamma(Z)$ and $\phi_\beta(Z)$ against GDP values

Before any policy shock is introduced to the model, the local economy for Bugala Island is in the 12th percentile of this distribution. The distribution has a median value of 16.38, which I assign as the value of Z_{med}, and a standard deviation of 1.176. Empirically estimating the slope parameter Z_{slope} is not possible given the limitations of the data. I follow the approach used in Garchitorena et al. (2017) by assigning a value for the slope parameter equal to 10% of the difference between the minimum and maximum values of the distribution. The steepness of the curve around the median value of the curve shown in Figure A.2 depends on the value of the slope parameter.

2.B Constructing the Next-Generation Matrix (NGM) Used to Derive R_0

To motivate the discussion here, I consider a fixed, homogeneous population of N individuals that are either susceptible to (denoted as S) or are infected with (denoted as I) a generic disease. Population shares for susceptible and infected individuals are written as $s = {}^{S}/_{N}$ and $i = {}^{I}/_{N} = 1 - s$, respectively. The disease has the following transmission characteristics:

- The effective contact rate, denoted as b, is the rate at which the disease is passed from an infected individual to a susceptible individual. This rate is a product of the number of infections per contact and the number of contacts per time period.

- The rate of recovery, denoted as a, is the rate at which an infected individual becomes susceptible to the disease. The inverse of a is the mortality rate for the disease and can be thought of as the rate at which the disease "dies off" in an infected individual.

We can write the equation that represents how the population share of infected individuals changes over time as

$$\frac{di}{dt} = bsi - ai \tag{2.27}$$

and use this equation to find the steady-state values of i; that is, the values for which i does not change over time, which is also when Eq. (2.27) is equal to zero and thus can be solved as a quadratic equation with two roots. At the disease-free equilibrium (DFE), the entire population is free of infection

$$i_{DFE} = 0 \tag{2.28}$$

while at the endemic equilibrium (EE), a share of the population is infected according to the equation

$$i_{EE} = 1 - \frac{a}{b} \tag{2.29}$$

while the remaining share of the population is susceptible to the disease.

The basic reproduction number, or R_0, is a dimensionless value that is defined as the average number of secondary cases arising from one new infection when the entire population is susceptible (Diekmann, Heesterbeek, and Roberts, 2009). R_0 is always a positive number, as it is not possible to have a negative number of secondary cases or a negative infection rate. Furthermore, the value of R_0 tells us which of the two equilibria—the DFE or the EE—is stable. If $R_0 < 1$, the DFE is stable and i will decline toward zero over time. On the other hand, the EE is stable whenever $R_0 > 1$.

To identify the expression for the R_0 for this generic disease in the case of a homogeneous population, we take the derivative of Eq. (2.27) with respect to i around the DFE (i.e., where $i = 0$ and thus $s = 1$, which is the case when the entire population is susceptible). We obtain

$$\left.\frac{\partial \dot{i}}{\partial i}\right|_{i=0} = b - a \tag{2.30}$$

which we assume is positive, because we know that R_0 is a positive number. We can therefore write the R_0 for equation (2.27) as

$$R_0 = \frac{b}{a} \tag{2.31}$$

which we can use to more formally restate the relationship between R_0 and the two equilibria for the system of disease dynamics. Whenever $a > b$, R_0 will be less than 1 and the DFE will be stable, with i trending toward zero over time and remaining at that level until the value of a or b changes. Whenever $b > a$, R_0 will be greater than 1 and the EE will be stable, with

i trending toward i_{EE} and remaining at that level until the value of either a or b changes.

A Heterogeneous Population

Now consider that the same population of N individuals can be divided into two closed subpopulation groups (i.e., a member of one subpopulation cannot transfer to the other subpopulation), and the two groups are heterogeneous such that the two rates identified above vary across the two groups (i.e., $a_1 \neq a_2$ and $b_1 \neq b_2$). The system of equations

$$\frac{di_1}{dt} = b_1 s_1 i_1 - a_1 i_1 \tag{2.32}$$

$$\frac{di_2}{dt} = b_2 s_2 i_2 - a_2 i_2 \tag{2.33}$$

represents transmission characteristics for the same generic disease introduced above. This system of equations has two equilibria that can be found by setting the left sides of Eqs. (2.32) and (2.32) equal to zero and solving for the roots of the resulting quadratic equations. The first equilibrium point is the disease-free equilibrium (DFE), which exists when infection rates for both subpopulation groups are equal to zero. The endemic equilibrium (EE) exists where

$$i_{1,EE} = 1 - \frac{a_1}{b_1}$$

$$i_{2,EE} = 1 - \frac{a_2}{b_2}$$

and the remaining population is susceptible to the disease. For such scenarios with heterogeneous groups within a population, the R_0 for the disease is the spectral radius (i.e., the "dominant" eigenvalue, or eigenvalue that is largest in absolute value) of the next-generation matrix (NGM) constructed using the above system of equations. The NGM consists of a "numerator" matrix, which I denote as $\mathcal{F}$, and a "denominator" matrix, which I denote as

$\mathcal{V}$. To construct these matrices, we first divide the above system in two by separating terms associated with transition into each group with the numerator matrix and terms associated with transition out of each group with the denominator matrix. Specifically, we can rewrite Eqs. (2.32) and (2.33) as

$$\frac{di_1}{dt} = \underbrace{b_1 s_1 i_1}_{F_1} - \underbrace{a_1 i_1}_{V_1} \tag{2.34}$$

$$\frac{di_2}{dt} = \underbrace{b_2 s_2 i_2}_{F_2} - \underbrace{a_2 i_2}_{V_2} \tag{2.35}$$

where

$$F = \begin{bmatrix} F_1 \\ \\ F_2 \end{bmatrix} \tag{2.36}$$

and

$$V = \begin{bmatrix} V_1 \\ \\ V_2 \end{bmatrix} . \tag{2.37}$$

which can then be linearized around the DFE as follows. The numerator matrix for the NGM is a square matrix of partial derivatives that can be written as

$$\mathcal{F} = \begin{bmatrix} \frac{\partial F_1(i_1^*,i_2^*)}{\partial i_1} & \frac{\partial F_1(i_1^*,i_2^*)}{\partial i_2} \\ \\ \frac{\partial F_2(i_1^*,i_2^*)}{\partial i_1} & \frac{\partial F_2(i_1^*,i_2^*)}{\partial i_2} \end{bmatrix} = \begin{bmatrix} b_1 & 0 \\ \\ 0 & b_2 \end{bmatrix}$$

where each partial derivative term is evaluated by setting infection rates equal to zero (denoted using asterisks). Similarly, the denominator matrix for the NGM can be written as

$$\mathcal{V} = \begin{bmatrix} \frac{\partial V_1(i_1^*, i_2^*)}{\partial i_1} & \frac{\partial V_1(i_1^*, i_2^*)}{\partial i_2} \\ \\ \frac{\partial V_2(i_1^*, i_2^*)}{\partial i_1} & \frac{\partial V_2(i_1^*, i_2^*)}{\partial i_2} \end{bmatrix} = \begin{bmatrix} a_1 & 0 \\ \\ 0 & a_2 \end{bmatrix}$$

where the inverse matrix $\mathcal{V}^{-1}$ exists and can be written as

$$\mathcal{V}^{-1} = \begin{bmatrix} \frac{1}{a_1} & 0 \\ \\ 0 & \frac{1}{a_2} \end{bmatrix} .$$

The NGM for the system of equations represented by Eqs. (2.32) and (2.33) is

$$\mathcal{F}\mathcal{V}^{-1} = \begin{bmatrix} \frac{b_1}{a_1} & 0 \\ \\ 0 & \frac{b_2}{a_2} \end{bmatrix} \tag{2.38}$$

which leaves us with the final step of finding the spectral radius, or dominant eigenvalue, of the NGM. Consequently, we can write the R_0 for this system as

$$R_0 = \rho(\mathcal{F}\mathcal{V}^{-1}) = \max\left\{ \left|\frac{b_1}{a_1}\right|, \left|\frac{b_2}{a_2}\right| \right\} \tag{2.39}$$

which is as much as we can conclude until we assign values to the system parameters.

2.C Equations of the EBL Model

The tables below contain the equations that comprise each component of the EBL model. The Epi component contains 9 equations, the Bio component contains 1 equation, and the LEWIE component contains 350 equations. Each equation corresponds to a variable whose value is identified in the solution process.

Table C.1: Equations and variables for the Epi component of the EBL model

Equation Type (Number of Eqs.)	Equation Statement	Variable
State Equation: Household Infection Status (4)	$\dot{I}_h = \beta(Z)\tau_h\epsilon_h Y(1 - I_h) - \gamma(Z)I_h$	I_h
State Equation: Snail Infection Status (1)	$\dot{Y} = \chi(1 - Y)\sum_{h=1}^{H} g_h\tau_h\epsilon_h I_h - \mu Y$	Y
Household Exposure Time (4)	$\tau_h = \bar{\tau}_h + \frac{L_{h,fish}}{L_{h,fish,baseline}}$	τ_h

Table C.2: Equations and variables for the Bio component of the EBL model

Equation Type (Number of Eqs.)	Equation Statement	Variable
State Equation: Fish Stock (1)	$\dot{X} = Xr_{fstock}(1 - \frac{X}{K_{lake}}) - HARV$	X

Table C.3: Equations and variables for the LEWIE component of the EBL model

Equation Type (Number of Eqs.)	Equation Statement
Value-Added Prices (24)	$PVA_{g,h} = PVA(p_g; idsh_{g,gg,h})$
Value-Added Output (24)	$QVA_{g,h} = QVA\begin{pmatrix} FD_{g,f,h}; fshare_{g,f,h}, \\ pshift_{g,h}, stock_g, stockbeta_g \end{pmatrix}$
Factor Demand (96)	$FD_{g,f,h} = FD\begin{pmatrix} r_{g,f,h}, w_f, PVA_{g,h}, QP_{g,h}; \\ theta_{f,h}, stockbeta_{g,h}, fshare_{g,f,h} \end{pmatrix}$
Output (6)	$QP_{g,h} = QP(QVA_{g,h}, vash_{g,h})$
Intermediate Demands (96)	$ID_{g,f,h} = ID(QP_{g,h}, idsh_{g,f,h})$
Household Consumption (24)	$QC_{g,h} = QC\begin{pmatrix} p_g, HHEXP_h, trout_h, sav_h, expout_h; \\ util\_sh_{g,h}, good\_elas_h \end{pmatrix}$
Household Income (4)	$HHEXP_h = HHEXP\begin{pmatrix} r_{g,f,h}, fd_{g,f,h}, w_{f,h}, \\ efflabsup_h; exinc_h \end{pmatrix}$

Continued on next page

Table C.3 – continued from previous page

Equation Type (Number of Eqs.)	Equation Statement
Household Marketed Surplus (24)	$HMS_h = HMS(QP_{g,h}, QC_{g,h}, ID_{gg,g,h})$
Economywide Marketed Surplus (6)	$VMS = VMS(p_g, HMS_{g,h})$
Household Factor Marketed Surplus (8)	$HFMS_h = HFMS(HFSUP_{f,h}, FD_{g,f,h})$
Economywide Factor Marketed Surplus (2)	$VFMS = VFMS(HFMS_h)$
Transfers out (4)	$TROUT_h = TROUT(HHEXP_h; trout\_sh_h)$
Household Savings (4)	$SAV_h = SAV(HHEXP_h; sav\_sh_h)$
Exogenous Expenditures of the Household (4)	$EXPROC_h = EXPROC(HHEXP_h; exproc\_sh_h)$

Continued on next page

Table C.3 – continued from previous page

Equation Type (Number of Eqs.)	Equation Statement
Output for Composite Goods (Armington Function) (1)	$QP\_Comp = QP\_Comp\left(\begin{array}{l} QP_{g,h}, Imports_g; \\ armg\_shift_g, delta_g, rho_g \end{array}\right)$
Prices for Composite Goods (Armington Function) (1)	$P\_Comp = P\_Comp(QP_{g,h}, p_g; delta_g, rho_g)$
Imports (1)	$Imports_g = Imports(QP\_Comp, QP_{g,h}, p_g, Imports_g)$
Household Labor Supply (4)	$HFSUP_h = HFSUP\left(\begin{array}{l} Labtime_B L_h, I_h, w_{f,h}; \\ \alpha, lab\_elas_h \end{array}\right)$
Consumer Price Index (4)	$CPI_h = CPI(p_g, QC_{g,h})$
Household Real Income (4)	$RY = RY(HHEXP_h, CPI_h)$

Chapter 3

Simulations of Policy Shocks

3.1 Introduction

In this chapter, I present the results from simulations of three types of policy interventions across the ecology, economic, and disease domains using the model developed in Chapter 2.

The first policy that I study is an agricultural investment intervention designed to raise household incomes in the local economy by increasing yields in the oil palm sector. The oil palm sector in Kalangala District is the product of a public-private partnership between the government of Uganda and *Bidco*, a private company based in Africa. Oil palm trees were first planted in 2005 on the 6,500 hectare "nucleus" estate operated by the private partner (Nsamba-Gayiiya and Kamusiime, 2015).[1] Operating as contract farmers, local households produce oil palm fresh fruit bunches (FFBs) on a combined 3,500 hectares of land. Households sell their output to the nucleus estate, which then transports the FFBs out of the district for processing into palm oil. The price that the households receive for the FFBs is determined by a national committee using a formula that depends on costs associated with processing raw FFBs, transportation costs, and the world price of crude

[1]The term "nucleus" refers to the relationship between the centralized production facility that is run by the large private investor and smallholder producer households that sell their output to the nucleus estate.

palm oil (Masiga, Khauka, and Nabatanzi, 2019).

The second intervention I consider is a fisheries management policy designed to improve returns to future fishing effort by regulating current fishing effort via a limited entry program for fishing boats. The fisheries of Lake Victoria have been characterized as overfished for over three decades (Secretariat, 2016). Several attempts to regulate fishing effort in the sector have met with limited or no success. When compared to their counterparts in more developed areas of the world, one characteristic feature of the institutions in charge of fisheries management is a relatively low capacity for regulating fishing effort. Consequently, the options available to policymakers that seek to reduce overfishing are limited.

The third policy intervention is a health-focused program that reduces infection rates for the disease Schisto using the drug Praziquantel. Schistosomiasis infection is prevalent across Kalangala District (Tukahebwa et al., 2013; Standley, Adriko, Arinaitwe, et al., 2010; Standley, Adriko, Besigye, et al., 2011). This is true despite ongoing efforts to provide treatment via MDA campaigns that target schools and locations in the community such as health centers and fishing landing sites.

These policies were chosen because they are highly relevant to the economy represented in the data and because they are examples of policy tools used to pursue common objectives in the domains of economic development, fisheries management, and public health. Each of the policies that I model in this chapter has a primary objective that is focused on one of the three domains. However, each policy also has the potential to produce ancillary consequences—either benefits or costs—for other domains of the local economy. For example, annual MDA programs may have knock-on effects for the local economy by increasing the productivity of one unit of labor time. Identifying the ancillary consequences of these policies provides a more complete understanding of the trade-offs that may result from each type of policy intervention.

3.2 A Review of the Methodology

The results presented in this chapter are generated by combining two methods in the literature that rely on household survey data and locally focused general equilibrium models to study a variety of policy interventions. In both approaches, means and standard errors are directly estimated for exogenous parameter values, such as production factor shares and expenditure shares, using survey data collected from households and businesses in the local economy. Values for the endogenous parameters, such as factor demands, consumption levels, endowment levels, and market aggregate levels, are identified alongside the initial guesses for the solutions to the model.

In the first approach, the baseline model of the local economy is constructed using the point estimates for the exogenous parameters, model assumptions, and model statements. Two examples of studies that utilize this approach are Gilliland, Sanchirico, and Taylor (2019) and Lindsay et al. (2020), both of which link the model of the local economy to a dynamic model of the fish stock. In both of these studies, a policy shock is introduced to the baseline model and the model is solved again to obtain updated, post-shock solution values, usually stated as values for year 1, or 1 year after the policy shock. The model of the fish stock, which is written as a step equation between years, is used to solve for the level of fish stock in year 2 using the level of harvest for year 1. This process repeats over a study period of years (Manning, Taylor, and Wilen, 2018; Gilliland, Sanchirico, and Taylor, 2019; Lindsay et al., 2020). By using only point estimates for parameter values, a single time path for a given outcome of interest is produced. The estimated standard errors are utilized in the econometric analysis for determining significance, but do not play a role in the simulation analysis.

In the second approach, before-after effects of policy interventions are studied using the point estimates *and* the standard errors for the estimated parameter values (Taylor and Filipski, 2014; Taylor, Filipski, et al., 2016; Filipski and Belton, 2018). Such studies utilize Monte

Carlo techniques to construct N sets of parameter values by sampling from distributions of the exogenous parameters, defined using the aforementioned point estimate and standard errors. Each set of drawn parameter values is used to obtain a corresponding set of equilibrium values of the baseline model of the local economy. These equilibrium values are consistent with model assumptions and values observed in the survey data, resulting in N draws, or realizations, of the baseline model of the local economy. For each draw of the baseline model, a policy shock is introduced and the updated model solutions are found, which can be used to calculate before and after differences in outcomes. For a given outcome of interest, the N values found in the previous step can be used to calculate an average value over the N draws. Additionally, confidence bounds can be obtained by ordering the N values and identifying the desired percentile values (e.g., 5th and 95th).

I combine these two approaches by producing a time path for a given outcome of interest for each draw of the baseline model. To do this, I first construct the baseline EBL model, taking care to preserve the four links between the three component models. The objective of this step is to obtain baseline solutions for the EBL model such that equilibrium is reached within each component model and between component models. Absent any changes to parameter values in the EBL model, including those that result from a simulated policy shock, the EBL model will remain in equilibrium. I then introduce a policy shock to the baseline EBL model and solve for the updated solutions for the Epi and LEWIE components of the model for the first year after the shock. I solve for the level of the fish stock in the second year using the level of harvest identified in the solutions from the first year. This process repeats for each year over the 10-year study period.

3.2.1 Preparing the Baseline Model For Analysis

Before a policy shock can be introduced, I obtain baseline values for the EBL model such that the model is in equilibrium within and between the three component models. To do this, I first draw $N = 1,000$ values for each of the exogenously determined parameters of the LEWIE component using the means and standard errors for those parameters. I then solve for the remaining parameter values that are endogenous to the LEWIE component at the same time that I solve for initial guesses for the solutions to the LEWIE component. However, it is not sufficient to find the solution values for the LEWIE component in isolation. Because of the links between the LEWIE and Epi components, it is necessary to solve both components simultaneously.

Link #1: Aggregate Output

The first link between component models is portrayed by defining the exposure rate parameter, β, and the parasite-human host mortality rate parameter, γ, as functions of aggregate output. This modeling choice reflects the fact that higher levels of wealth at the community level correlate with increased capacity for *public* investment in treatment and prevention for Schisto infection.

Link #2: Exposure Time

The second link between component models is a novel addition of a household-specific measure of exposure time to the disease, denoted as τ_h. This parameter is composed of a time-varying component—the amount of fishing labor time supplied by the household—and a time-invariant component, which accounts for activities such as time spent collecting water that are correlated with disease transmission but are not modeled explicitly.

Link #3: Effective Labor and Labor Time

Whereas the first two links allow me to account for the impact that economic activities have on disease prevalence, the third link allows me to account for the impact that disease prevalence has on an important measure of economic activity: the supply of effective labor.

The equation

$$E_h = L_h(1 - I_h\alpha) \tag{3.1}$$

captures this relationship.

Link #4: Total Harvest and the Fish Stock

The fourth link between component models accounts for the relationship between fishing effort and future fish stocks. The equation

$$\dot{X} = Xr_{fstock}(1 - \frac{X}{K_{lake}}) - HARV \tag{3.2}$$

describes the growth of the fish stock over time. This equation allows me to account for the natural growth process of the fish stock (described as a logistic process) and the pressure on the fish stock that results from harvest obtained by the fishing sector in the local economy. I use the amount of harvest as a proxy for fishing effort, as is common in the literature (e.g., Gilliland, Sanchirico, and Taylor, 2019).

I assume that the fish stock is at equilibrium at baseline, which means that $\dot{X} = 0$ and, consequently, that the value harvested at baseline (converted to kilograms) is equal to the natural growth of the fish stock (in kilograms). I convert the value of baseline harvest to kilograms using a composite price of 5,519 UGX.[2] This results in a quadratic equation with two positive roots. I then solve for the baseline level of the fish stock by finding the smaller of the two positive roots from the resulting quadratic equation.[3]

[2]This harvest-share weighted composite price was calculated using historical price and harvest data shared with me by the Kalangala District office of the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF)

[3]The larger of the two roots is greater than the maximum sustainable yield of $K/2 = 10,700$ metric tons that can be identified from the logistic growth function. I use the smaller of the two roots, since the larger value would be inconsistent with the documented history of overfishing on the lake Witte et al., 1992; Kolding et al., 2014.

3.2.2 Baseline Conditions of the Local Economy

The Monte Carlo procedure produces 1,000 realizations of the local economy, which can be used to produce summary statistics for key measures in the domains of the economy, the ecosystem, and disease prevalence.

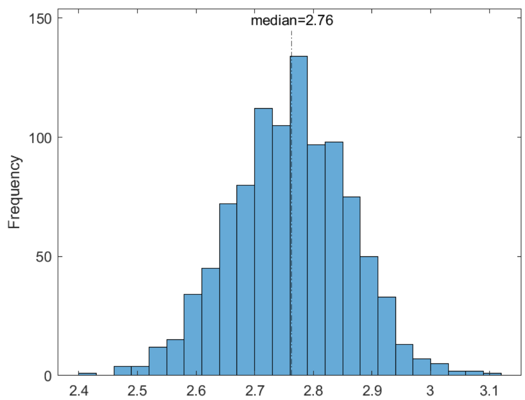


Figure 3.1: Baseline Values of R_0

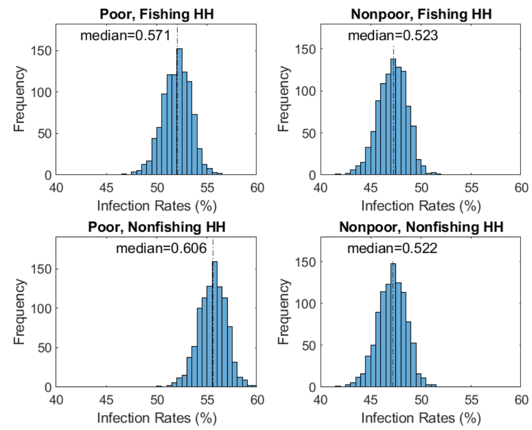


Figure 3.2: Baseline Household Infection Rates

Across the 1,000 sampling scenarios, the median value of R_0 is equal to 2.76, which is in line with values used in previous studies on Schisto (Castonguay et al., 2020; Halstead et al., 2018). Since this value is greater than 1, we can conclude that the endemic equilibrium (EE) for the Epi component is stable, and therefore the disease will persist in the environment and human population. Unless and until the underlying conditions that inform the values of the parameters in the Epi component change significantly such that the value of R_0 falls below 1, the EE will remain stable. Whether a policy will result in the switch from the EE to the disease-free equilibrium (DFE) as a result of changes in the underlying conditions of the parameters in the Epi component is an open question, but if it does, the prevalence of the disease in the environment and in the human population will trend towards zero.

The underlying conditions that inform the values of the parameters in the Epi component include the mortality rate of the snail in the environment (μ), the mortality rate of the parasite in the human host (γ), and the rate of exposure to the disease (β). Following previous literature, I model both γ and β as functions of aggregate output (see Appendix A in Chapter 2). I also include a novel, household-specific measure of exposure time to the disease (τ_h) that includes a time-varying measure of fishing labor time. All three of these parameters are functions of the local economy and thus can vary in response to policy shocks.

Using household's population shares and the values shown in Figure 3.2, I calculate the median population-weighted community infection rate to be 55.1%, which is comparable to infection rates observed in recent years in Kalangala District (Standley, Adriko, Besigye, et al., 2011). Poor households have a median higher infection rate than nonpoor households, reflecting the effect of higher income on access to treatment and prevention measures for the disease. The variation in household infection rates also reflects the fact that each household has a relative risk of exposure (and contamination), which is represented by the parameter ϵ_h in the Epi component equations (see Chapter 2). Consequently, poor nonfishing households have a higher median infection rate than poor fishing households because their relative risk of exposure to the disease is higher than poor fishing households.

Table 3.1: 25th and 75th Percentile Averages of Baseline Levels of R_0, Fishing Labor Time, and Aggregate Output.

Percentile of R_0	R_0	Fish Stock	Daily Per Capita Aggregate Output
25th	2.69	27.3%	\$2.21
75th	2.83	27.1%	\$2.01

Notes: Fish stock reported as share of carrying capacity. Daily per capita aggregate output reported in 2017 US dollars.

I use the set of 1,000 realizations of the local economy to evaluate whether some characteristics of the model vary over values of R_0. After arranging the observations in a table format, I sort all rows so that the values of R_0 are in ascending order. I then identify which rows correspond to the 25th and 75th percentiles (interquartile range) of the sorted data. I generate averages using 50 observations in the neighborhood of the 25th and 75th percentiles, and I use these averages to compare characteristics of the model on either side of the median value of R_0.

Table 3.2: 25th and 75th Percentile Averages of Baseline Levels of Sector Output.

Percentile of R_0	Sector Output (% Share of Aggregate Output)					
	Crop	Livestock	Fish	Oil Palm	Retail	Services
25th	11.3	11.1	12.5	29.3	16.7	19.1
75th	11.7	12.0	13.6	25.3	17.9	19.6

Notes: Shares sum to 100% across rows.
Source: Original Data.

Smaller values of R_0 correspond with slightly larger values of the fish stock, which suggests the potential for ancillary benefits to the ecosystem from reducing the prevalence of Schisto. Output in the oil palm sector is higher for smaller values of R_0, while output in the fishing and livestock sectors stays flat across the interquartile range, suggesting that oil palm may be a substitute for these sectors for employing factors of production, including labor, in the local economy.

3.2.3 Production

At lower levels of R_0, nonfishing nonpoor households engage more in oil palm production and less production in all other sectors relative to higher levels of R_0, while poor fishing households shift away from livestock (see Table 3.3). The few differences noted above across the 1,000 realizations of the model may be a consequence of the size of the standard errors for the estimated parameters.

3.2.4 Simulating Policy Shocks

With the EBL model in equilibrium within and between compopment models at baseline, I introduce a policy shock and solve for the updated values of the model in annual time

Table 3.3: 25th and 75th Percentile Averages of Baseline Output Shares of Household Production.

Household	Percentile of R_0	Productive Sector Output Shares (%)					
		Crop	Livestock	Fish	Oil Palm	Retail	Services
Poor, Fish	25th	6.1	9.1	52.6	13.1	3.4	15.6
	75th	6.2	8.6	53.0	13.4	3.3	15.5
Nonpoor, Fish	25th	5.7	7.4	45.1	18.3	8.6	14.9
	75th	5.5	7.4	45.3	18.4	8.7	14.7
Poor, Nonfish	25th	28.4	21.6	-	35.2	9.1	5.7
	75th	28.1	22.4	-	33.9	9.7	5.9
Nonpoor, Nonfish	25th	8.5	9.2	-	33.9	24.0	24.5
	75th	9.1	10.6	-	27.6	26.8	25.9

Notes: Shares sum to 100% across rows.
Source: Original Data.

steps over ten years. For each year, I find the equilibrium values for the LEWIE and Epi components simultaneously, usin

After repeating the simulation process for each set of drawn parameter values, I solve for 1,000 time paths for each outcome. I present results over the 10-year study period using box and whisker plots. A vertical bar represents the interquartile range of results for each year. The minimum and maximum values in each year are indicated by the whiskers that extend from the top and bottom of each box. The *median* values in each year are denoted by the horizontal line in the middle of each box and may differ from the value for the median time path, although the differences do not appear to be consequential.[4]

[4]The median value in a given year may differ from the value for the median time path due to nonlinearities in the system. I have only found evidence of minimal deviation between these two median values, suggesting no qualitative difference between results presented using either value.

3.3 Economic Domain: TFP Increase in Oil Palm

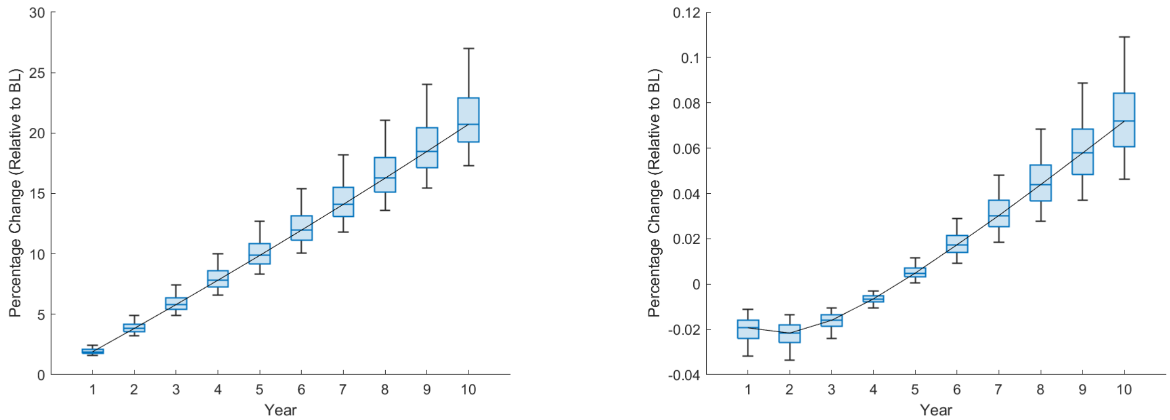
Agricultural extension services have been used in many developing countries as a strategy for improving the quality and productivity of the human capital input in the production process (Anderson and Feder, 2007). Because of the importance of extension services in agricultural development efforts, I consider an annual increase of 1% in total factor productivity (TFP) for oil-palm producing households, which represents the results of agricultural extension services that provide education and recurrent training for oil-palm producing households. I introduce this policy shock into the model by increasing the value of the shift parameter in the oil-palm production functions for the producer households.[5]

A local objective of this policy might be to reduce differences in yields between the operations of the private partner on the nucleus estate and production by the smallholder oil-palm producing households. Previous studies have identified gaps between actual and potential yields among independent oil palm-producing households relative to the nucleus estate in Indonesia (Jelsma et al., 2017; Hasnah, Fleming, and Coelli, 2004) and Ghana (Monzon et al., 2023). Ghanaian oil palm farmers sought greater access to extension services as a way to improve yields (Khatun et al., 2020). Agricultural extension services can be successful in improving productivity when there is a gap between observed yields and potential yields (Anderson and Feder, 2007).

3.3.1 Economic Impact of TFP Increase in Oil Palm Sector

Since the oil palm sector is directly targeted by the policy, *a priori* we expect that this sector will realize larger changes in output and input demand than the other sectors. Indeed, we observe this to be the case. Median output in the oil palm sector grew by 20% over the study period, with results ranging from 15% to 27%. The widening of the results over time

[5]It is possible that knowledge gained from extension services may be transferable to other sectors that households are active within. However, as oil palm is a cash crop, its production process may be sufficiently unique to limit such a transfer. Consequently, I do not model this transfer of knowledge across productive sectors.



(a) Oil Palm Sector

(b) Fishing Sector

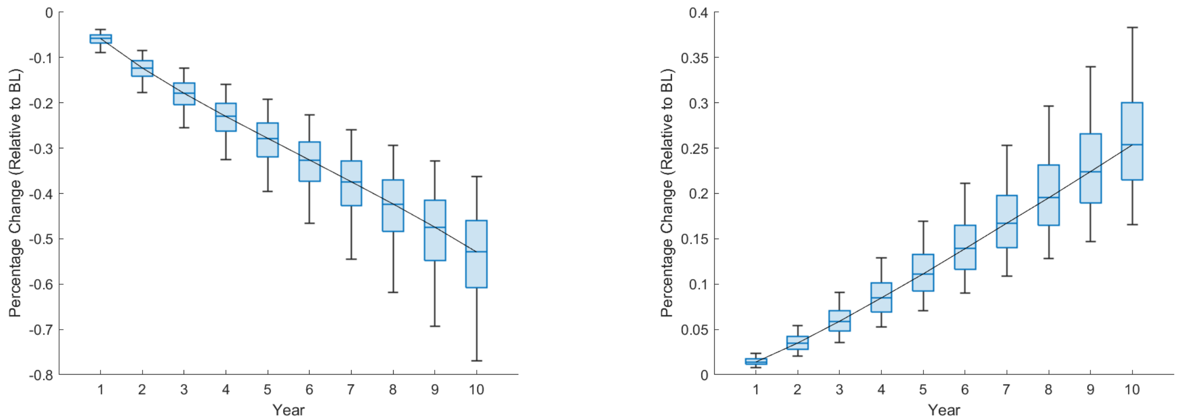
Figure 3.3: Percentage Changes in Oil Palm and Fishing Sector Output from TFP Shock

is due to the increase in the size of the policy intervention over time. In the first year, the intervention introduces a 1% increase in oil palm TFP, but by year ten the increase due to the intervention is 10.5% relative to baseline (due to annual compounding).

Output in the fishing sector initially declines in years one and two before reversing course and ending above baseline levels. Compared to changes in oil palm output, the percentage changes in fishing sector output are quite small—less than one-tenth of one percent above initial values by year ten. Fishing labor time declines, however, meaning that the increase in fishing output is due to the growth in the fish stock (since fishing capital, the other non-resource input in the sector, is fixed over the study period).

The decrease in fishing labor time is due to households shifting their labor to the oil palm sector. This result demonstrates the potential for a policy of the sort modeled here to incentivize the reallocation of labor away from hazardous working conditions such as those observed in the fishing sector.

However, the potential for labor reallocation away from the fishing sector depends on whether output from the local fishing sector is substitutable with imports. In the main specification of the model, the output price of fish is determined globally. When this is the case, an



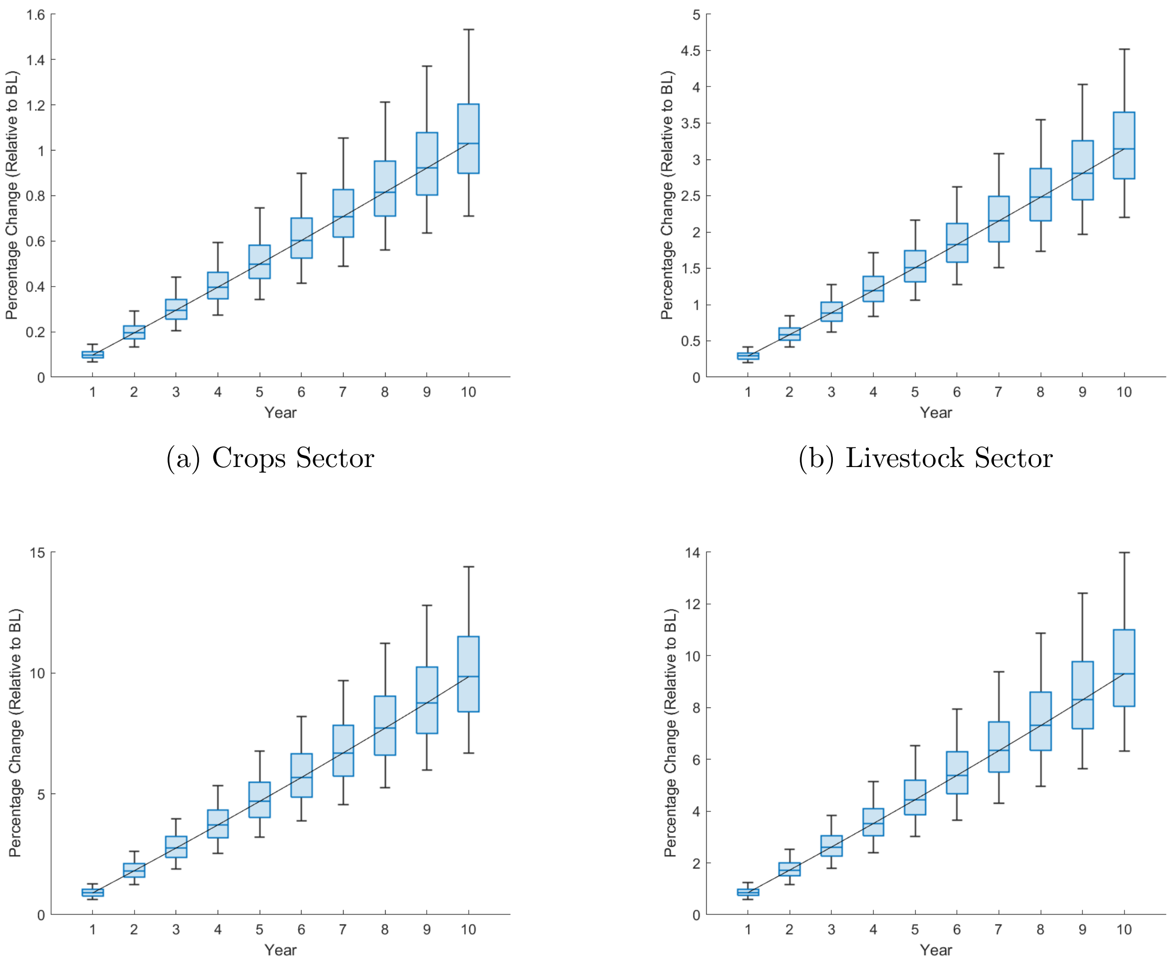
(a) Fishing Labor Time (b) Fish Stock

Figure 3.4: Percentage Changes in Fishing Labor Time and Fish Stock Levels from TFP Shock

increase in local demand for fish can at least partially be met with imports, which reduces pressure on the local fishing sector.

In Chapter 6, I consider how alternative model specifications may give rise to results that differ from those presented in this chapter. For example, in some settings where transaction costs are sufficiently high, the output price of fish is determined locally. In such a setting, rising household incomes due to a TFP shock to the oil palm sector would create pressure on the local fishing sector to produce more output than in the case where the output price of fish is determined globally. Consequently, in settings where the price of fish is determined locally, the TFP policy shock could actually lead to an *increase* in the amount of fishing labor time and, consequently, an increase in exposure time. Such a result would suggest that determinants of the output price of fish are factors that can also influence disease prevalence.

Although not directly targeted by the policy, output in the other four sectors also increases over the study period. These sectors are indirect beneficiaries of the policy effects that reverberate throughout the local economy. Identification of such knock-on results demonstrates a strength of the general equilibrium component of the model that is also characteristic of



(a) Crops Sector

(b) Livestock Sector

(c) Retail Sector

(d) Service Sector

Figure 3.5: Percentage Changes in Other Sector Output from TFP Shock

previous studies that focus on the local economy impact of policy shocks (see, for example, Taylor and Filipski, 2014).

The ripple effect of the TFP policy throughout the economy occurs because higher incomes allow households to spend more in the other sectors of the local economy. Real incomes increase for each of the four household types. Poor households experience disproportionately higher increases in real income than their nonpoor counterparts. Even fishing households directly benefit from the policy because they also produce oil palm.

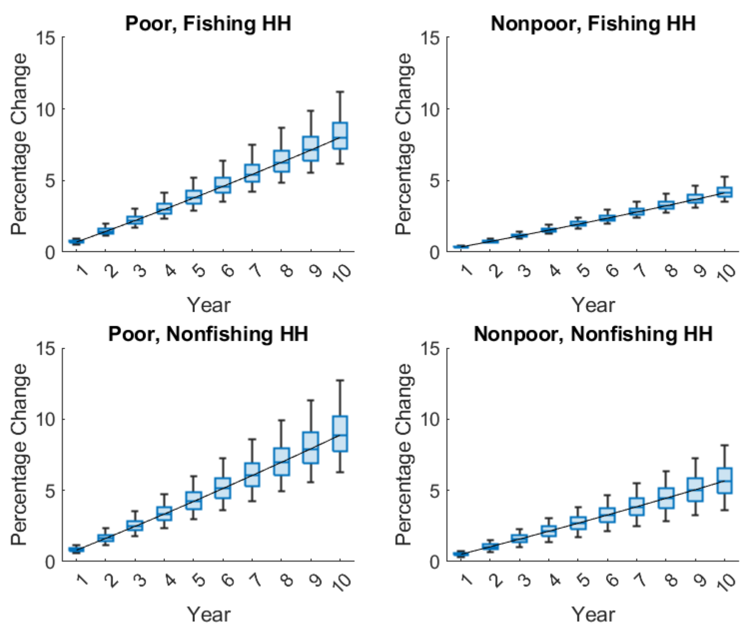


Figure 3.6: Percentage Changes (Relative to Baseline) in Real Household Incomes from TFP Shock

The increase in real household incomes suggests that the absolute poverty rate in the local economy falls by year ten (Figure 3.6).[6] This may occur because some households observed in the data have expenditures that were just below the cutoff line for assigning poverty status. Applying the increase in incomes to these observed households would result in these observations being reclassified as nonpoor. These results suggest that policies that improve

[6]Since we do not reclassify households as poor or nonpoor in between years, it is perhaps more accurate to think of the poverty rate calculated using the baseline conditions of the economy as a relative poverty rate.

yields among smallholder cash crop producers may have pro-poor consequences for economies in developing countries.

The changes in real household incomes are not driven entirely by the increase in oil palm TFP. For example, a household's income can also increase as it supplies more labor. We find that the supply of effective labor increases as a result of the TFP shock.

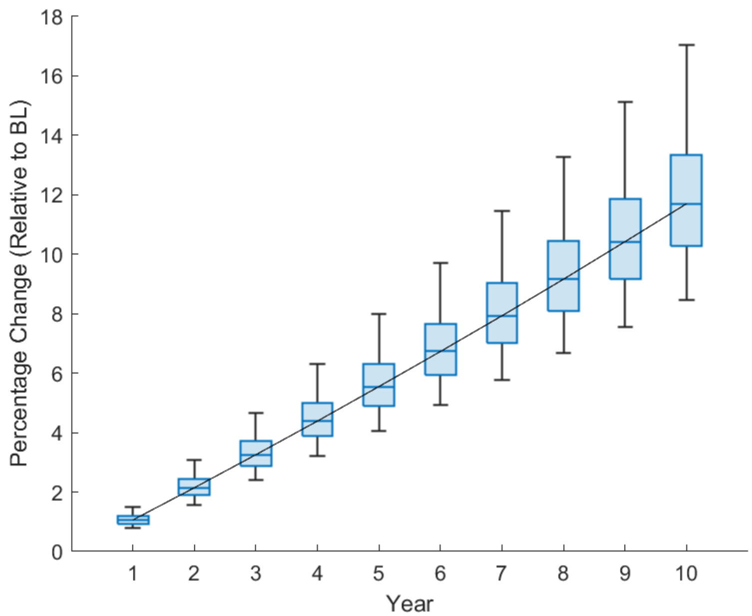


Figure 3.7: Percentage Changes in Supply of Effective Labor from TFP Shock

There are two reasons why the supply of effective labor may increase as a result of the TFP shock. First, the supply of labor is assumed to be highly elastic, owing to the high unemployment rate in the local economy (Taylor, Whitney, and Zhu, 2019). One consequence of a highly elastic labor supply is that an increase in demand for labor will result in an increase in the quantity of labor time supplied, all else equal, with minimal changes in the wage paid to effective labor. Additionally, with declining household infection rates, each unit of labor time supplied by the household becomes more productive. In Chapter 6, I explore how results presented in this chapter vary across values of the labor supply elasticity.

3.3.2 Impact on Health

A key strength of the Epi-Bio-LEWIE model is that it captures both the direct and ancillary effects of policies. For example, we have already seen that a policy shock that increases total factor productivity in the oil palm sector can result in an increase in the fish stock, which is an ancillary benefit for the ecosystem. In fact, we find that not only does the stock of fish increase over the study period, but fishing sector output increases at the same time that fishing labor time *decreases*.

This latter point ties into discussion of another ancillary consequence of the TFP policy shock. What, if any, impact might such a policy shock have on disease prevalence, and what are the mechanisms driving these results? To answer this question, we first observe that the value of R_0 declines steadily over the study period in response to the policy shock. We also observe that the size of the impact that the TFP shock has on R_0 depends on the baseline conditions of the economy.

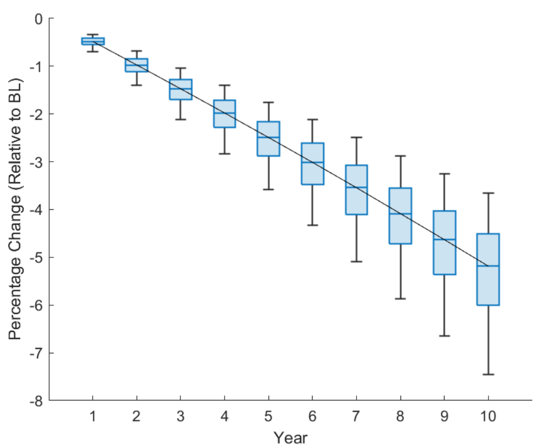


Figure 3.8: Percentage Changes in R_0 from TFP Shock

Infection rates decline for all households as a result of the increase in oil palm TFP. Fishing households experience a slightly larger reduction in infection rates due to reallocation of their labor away from fishing and toward the oil palm sector. The decline in infection rates for all households is driven primarily by the increase in aggregate output that results from increased yields in the oil palm sector.

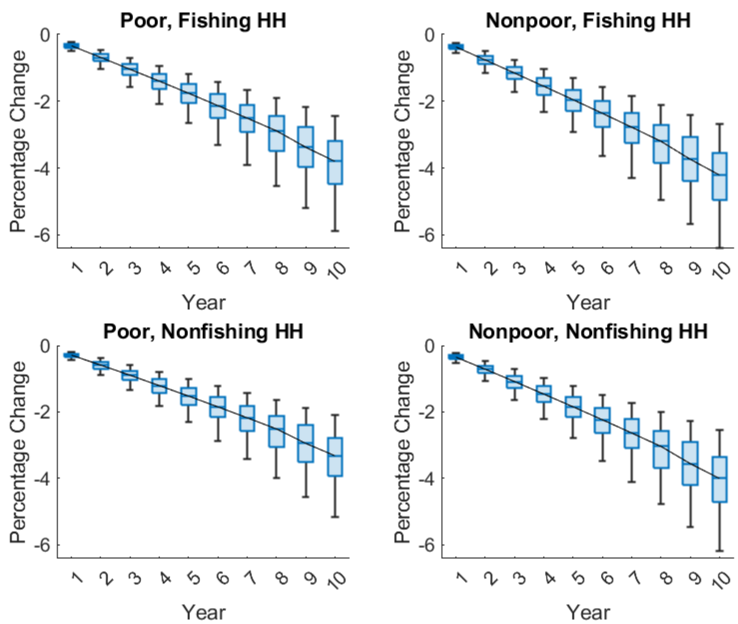
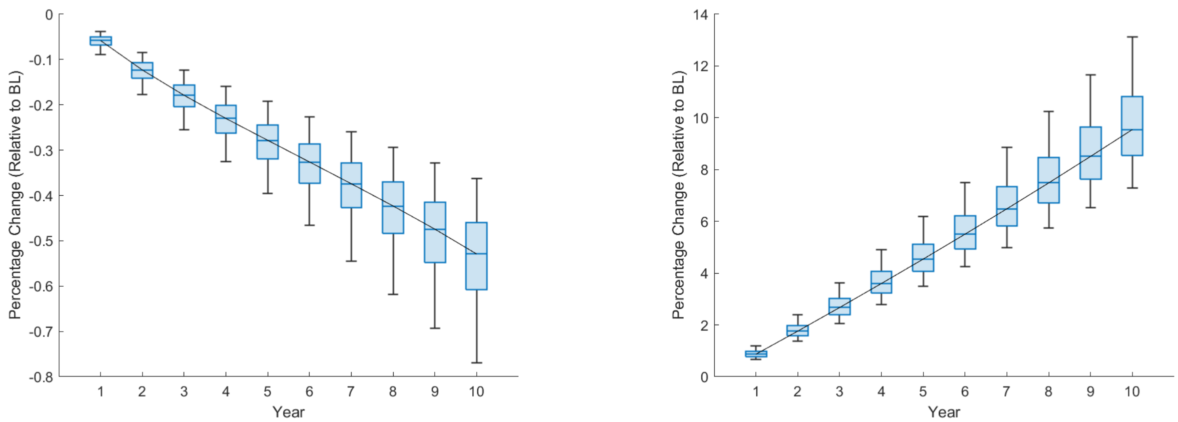


Figure 3.9: Percentage Changes (Relative to Baseline) in Household Infection Rates from TFP Shock

What are the mechanisms driving these changes in R_0 and household infection rates? The decline in R_0 shown in Figure 3.8 can be directly attributed to changes in aggregate output and fishing labor time. As shown in Figure 3.10b, aggregate output increases over the study period, with a final-period median value that is 9.3% above the baseline level of aggregate output.

In the EBL model, household exposure time consists of a fixed factor, due to background economic activities such as where households collect water, clean, and recreate, and a variable factor due to commercial fishing labor time. As exposure time declines in the model due to induced changes in fishing labor, so does an individual's likelihood of becoming infected with the parasite that causes the disease. Thus, household infection rates decline as household exposure time declines. But the degree to which changing the variable factor will have on disease prevalence is limited due to the role of the fixed factors (in the model), which in areas where Schisto is prevalent can be significant.



(a) Fishing Labor Time

(b) Aggregate Output

Figure 3.10: Percentage Changes in Fishing Labor Time and Aggregate Output from TFP Shock

A straightforward way for a household and communities to have access to a wider range of fixed factors in this context is by gaining more income. Higher household incomes increase the capacity for private investment in disease prevention and treatment. While I do not model how changes in private investment affect disease prevalence in this study, I do model how changes in public investment affects disease prevalence. Specifically, as households experience rising incomes, aggregate income increase. Aggregate income reflects the capacity for public investment in disease prevention and treatment and is explicitly accounted for in the Epi component.

In summary, the primary gains from the TFP policy shock are accompanied by two ancillary benefits. The first knock-on effect is observed in the (small) increase in the fish stock, which benefits the ecosystem as well as future returns to fishing effort. The second knock on effect is the reduction in household infection rates resulting from the increase in aggregate output and the reduction in fishing labor time.

3.4 Ecological Domain: Fisheries Management Policy (FMP) Reform

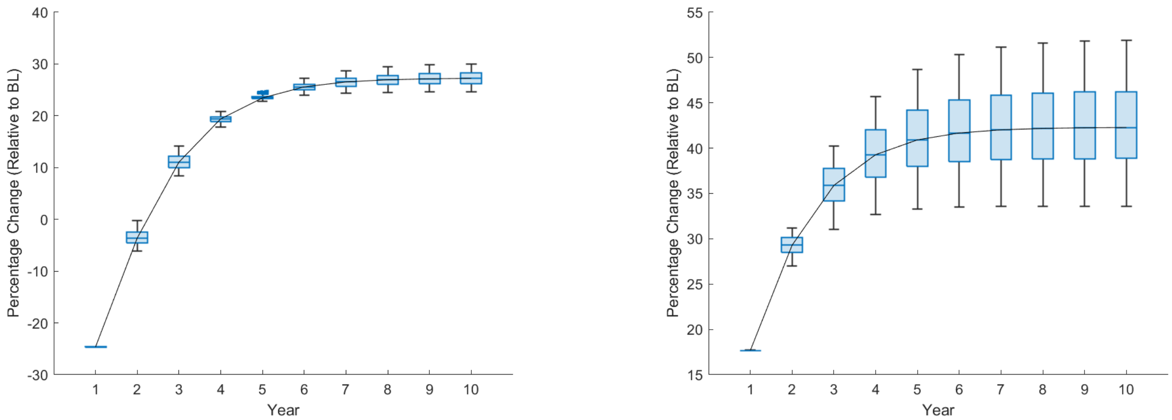
Overfishing on Lake Victoria is a decades-old problem that reduces future returns to fishing effort and contributes to degradation of the environment (Witte et al., 1992; Kolding et al., 2014; Nyamweya et al., 2022). In developing country settings where institutional capacity is underdeveloped, limited entry programs are among the few options available to policymakers seeking to regulate fishing effort (Purcell and Pomeroy, 2015). In the context of this study, limited entry programs may also have the ancillary benefit of reducing exposure time to the disease.

To investigate the impact that such FMP interventions may have on disease prevalence, I simulate the introduction of a limited entry program in the fishing sector for the local economy. The policy is modeled as a reduction of 25% in fishing capital that is sustained over the ten-year study period.

3.4.1 Ecological Impact of FMP Shock

The limited entry program results in an initial decline in fishing labor time that is nearly identical to the policy-imposed restriction on fishing capital. As a result of the decline in fishing effort, the fish stock begins to recover. Recovery of the fish stock leads to lower search costs, gradually drawing fishing effort back into the sector.

Since fishing capital is fixed over the study period, the return of effort back into the fishing sector can only take the form of additional fishing labor time. Capital effort is partially replaced by labor effort as a consequence of the FMP shock, and by the end of the study period, fishing labor time has rebounded with the fish stock, ending at approximately 13% above its baseline level. We also observe that while the baseline conditions of the economy do not determine the level of fishing labor time, they do determine the size of the effect that



(a) Fishing Labor Time (b) Fish Stock

Figure 3.11: Percentage Changes in Fishing Labor Time and Fish Stock Levels from FMP Shock

the FMP shock has on the stock of fish.

3.4.2 Economic and Health Consequences of FMP Shock

Real household incomes are also affected by the policy shock, with changes that are qualitatively similar to those reported in Gilliland, Sanchirico, and Taylor (2022), a study that looks at the impact of reforming an open access fishery in a developing country setting. Fishing households experience the largest changes due to the fact that the policy shock directly targets the fishing sector. Poor households experience a larger initial decline in their income compared to their nonpoor counterparts, suggesting that limited entry programs such as the one modeled here are regressive in the short term. Real income levels for all households recover to above baseline levels by year 10, with poor households realizing larger gains in their real incomes compared to nonpoor households. These latter results suggest that limited entry programs may be progressive in the long-term. In summary, the short-term regressive nature of such programs identified above suggest that limited entry programs should be accompanied by programs that provide economic support for poor households in the short-term.

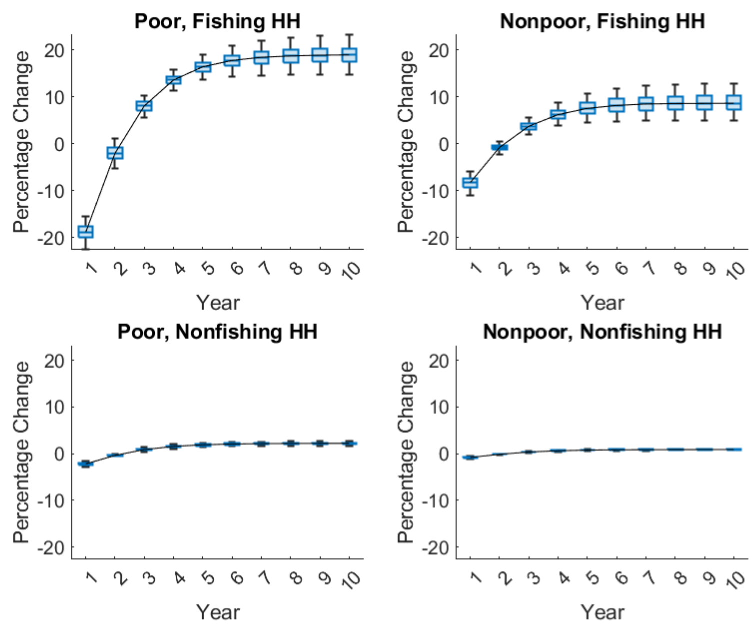


Figure 3.12: Percentage Changes (Relative to Baseline) in Real Household Incomes from FMP Shock

Even though non-fishing households are not directly affected (since they do not participate in the fishing sector), they still experience small initial declines in incomes. This occurs because each household participates in the local economy by purchasing output produced by other households. Consequently, the initial loss in real purchasing power for the fishing households has negative spillover effects by reducing income for the non-fishing households in the economy.

The increase in fishing labor time that results from the recovery of the fish stock represents an important ancillary effect of the FMP policy. Since fishing labor time is the variable component in a household's exposure time, the increase depicted in Figure 3.11a translates to a net increase in fishing households' exposure time to the disease.

Fishing households experience an initial drop in infection rates that is due to the initial withdrawal of fishing effort resulting from implementation of the FMP policy. However, as the recovery of the fish stock draws effort back into the fishing sector (Figure 3.11b), the return of effort to the sector (Figure 3.11a) translates to an increase in households' exposure

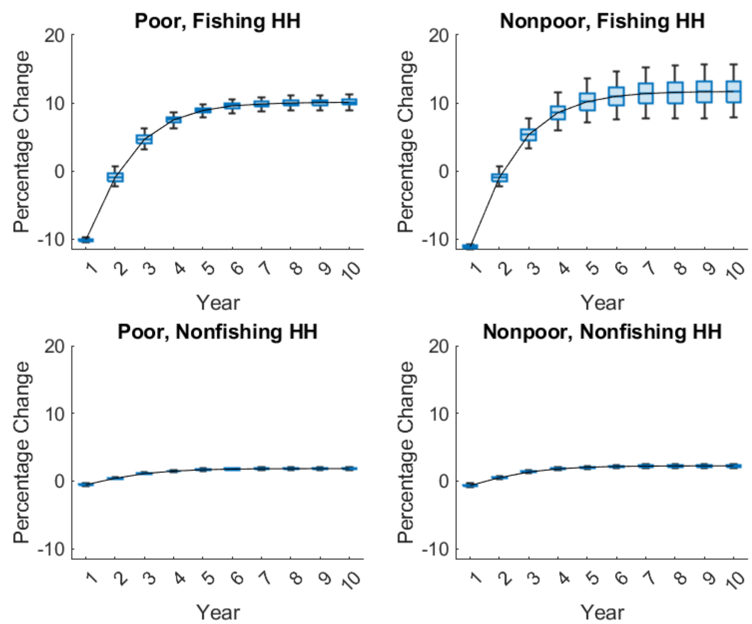


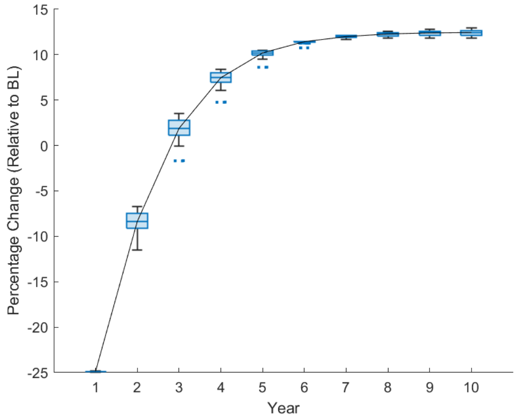
Figure 3.13: Percentage Changes (Relative to Baseline) in Household Infection Rates from FMP Shock

time, with fishing households ending up with higher infection rates by the end of the study period.

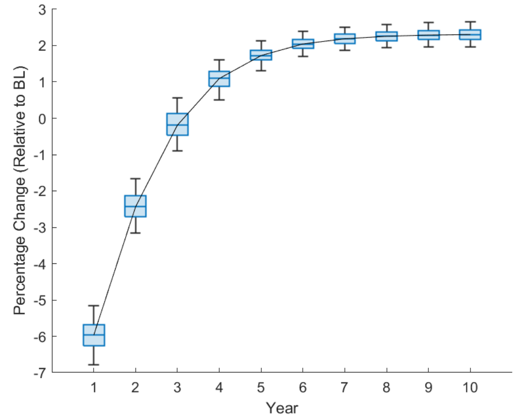
Compared to fishing households, non-fishing households experience relatively minor changes in their infection rates as a result of the FMP shock. Still, the initial uptick in non-fishing households' infection rates is noteworthy. This change is the result of the contraction in the economy that results from the FMP shock. Specifically, fishing sector output initially declines as a result of the policy, which drives the initial decline in aggregate output.

We also observe that the effect of the shock on household infection rates varies for nonpoor fishing households by year 10, whereas no other households experience such variation.

Although not directly targeted by the FMP shock, output levels in the other five sectors are also affected. As was the case in the Oil Palm TFP shock, these sectors are indirect recipients of policy effects that reverberate throughout the local economy. For crops, livestock, retail and service businesses, output initially declines as a result of the policy-induced contraction



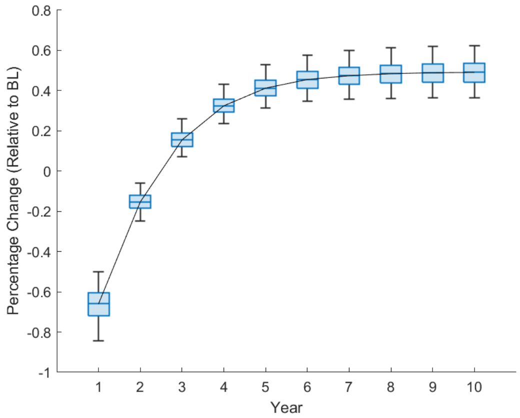
(a) Fishing Sector



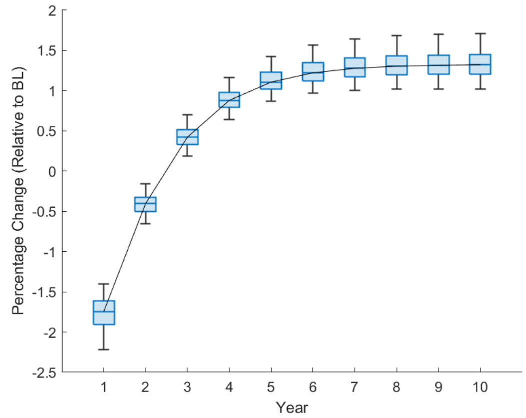
(b) Aggregate Output

Figure 3.14: Percentage Changes in Fishing Sector and Aggregate Output from FMP Shock

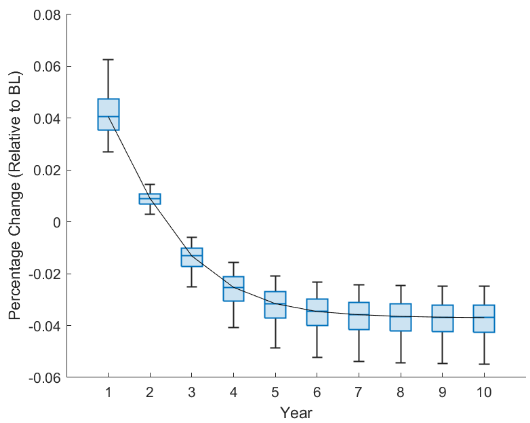
in the fishing sector. In contrast, the oil palm sector initially increases output as a result of the FMP shock. This is the result of labor reallocation from the fishing sector to the oil palm sector in response to the FMP shock. This is further evidence that the oil palm sector is a substitute to the fishing sector for labor allocation in the local economy.



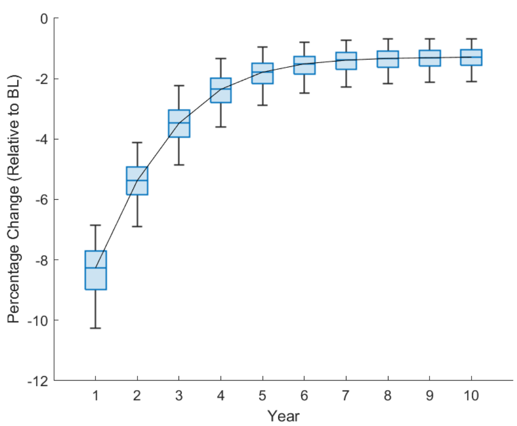
(a) Crops Sector



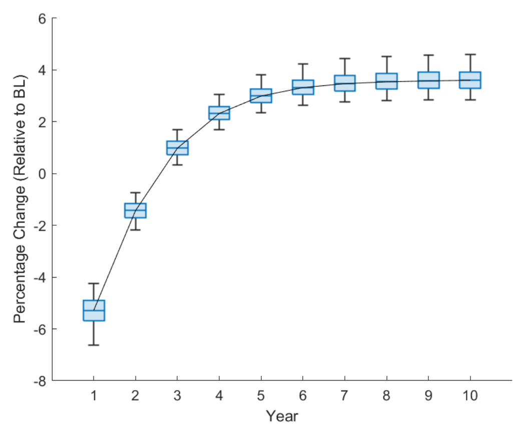
(b) Livestock Sector



(c) Oil palm Sector



(d) Retail Sector



(e) Service Sector

Figure 3.15: Percentage Changes in Other-Sector Output from FMP Shock

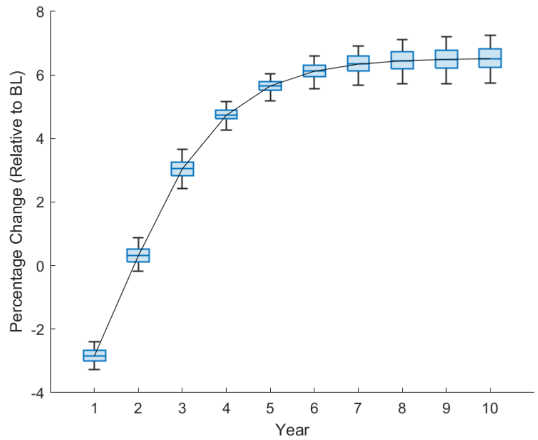


Figure 3.16: Percentage Changes in R_0 from FMP Shock

We find that R_0 increases over time, ending with a median value of approximately 6% above its baseline level. The median value of R_0 initially falls to 2.9% below the baseline value, which occurs because of the reduction in exposure time that results from the FMP policy shock. Specifically, the restriction on fishing capital leads to an initial decline in output by the local fishing sector, which is accompanied by a reduction in demand for fishing labor. The median initial decline in fishing labor time is nearly 25%—approximately the same size as the policy-induced reduction in fishing capital (3.11a). Aggregate output also declines initially, as shown in Figure 3.14b; the median value of aggregate output fell to 6% below the baseline level in year 1, and ended at approximately 2.6% above its baseline level. This initial decline in aggregate output partially offsets the effect of the reduction in fishing labor time on R_0.

3.5 Public Health Domain: MDA Program

The two prior policy examples focused on the oil palm and fisheries sectors, wherein we looked at the ancillary costs and benefits for disease prevalence associated with each policy. In this section, we focus on a policy that targets the disease explicitly and look at what the ancillary benefits and unintended consequences are for the economy and the ecosystem.

The third policy scenario that I consider is the implementation of an annual community-based MDA to reduce Schisto prevalence in the human population. MDA is a widely used method for combating Schisto because of the low cost of the drug *Praziquantel*. MDA programs are often conducted in schools because of program cost savings and because children are often the focus of treatment efforts. In high-prevalence areas, community-wide treatments can lead to additional reductions in infection rates (Lo et al., 2018).

I characterize the impact of an effective MDA program as an increase in the rate at which the household transitions out of the infected classification (Castonguay et al., 2020). I assume that, all else equal, implementation of the MDA program will produce an annual reduction in infection rates of 19.3% for all households in the local economy (King, Kittur, et al., 2020). I provide more details on the methodology used to model this policy shock in Appendix 3.A.

3.5.1 Impact on Disease Prevalence

By construction, the MDA program produces a decline in infection rates across households that is qualitatively similar to previous studies that model community-wide MDA programs and disease prevalence (Castonguay et al., 2020).

Household infection rates decline from their baseline levels of 50-60% and start to level off at the end of the study period. The asymptotic nature of the decline depicted in Figure 3.17 reflects the reality that elimination of the disease via MDA treatment alone is not feasible (King, Sturrock, et al., 2006; Inobaya et al., 2014).

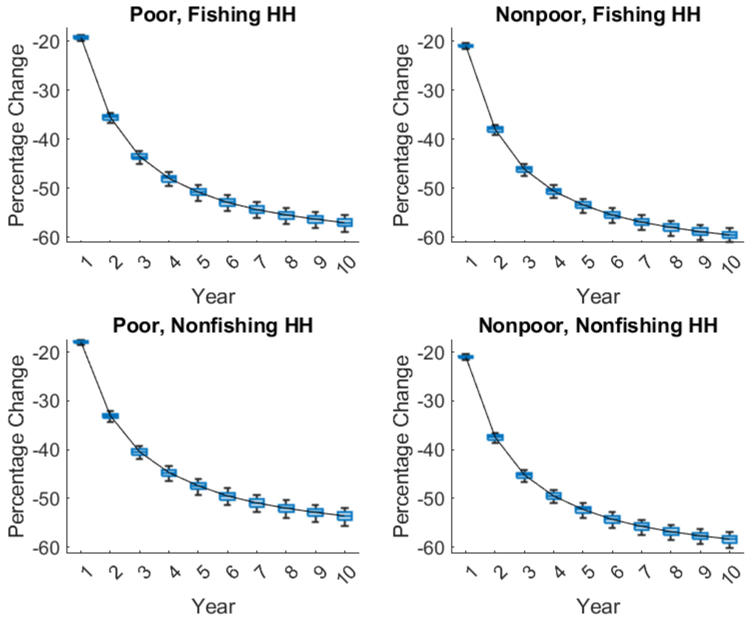


Figure 3.17: Percentage Changes (Relative to Baseline) in Infection Rates from MDA Shock

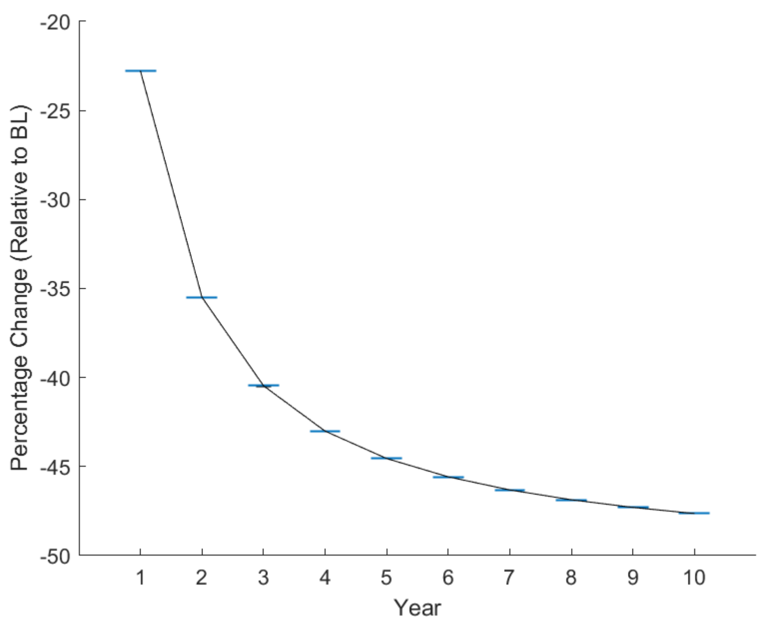


Figure 3.18: Percentage Changes in R_0 from MDA Shock

The value of R_0 declines by approximately 47% as a result of the MDA program. Starting from a median baseline value of 2.76, a decline of 47% results in a median value of 1.46 in year 10. This decline reflects the fact that Praziquantel, the drug used in treatment, effectively increases the mortality rate of the parasite in the human host. Additionally, the asymptotic nature of the decline over time (see Figure 3.18) suggests that the value of R_0 levels off near 1.46 absent any additional shocks to the system. Since the value of R_0 remains above 1, the EE will remain stable and we can conclude that the disease will remain in the human-natural environment over time, even with the MDA program active each year. This conclusion aligns with prior research suggesting that MDA programs alone aren't enough to eradicate the disease in a human-natural setting (King, Kittur, et al., 2020).

3.5.2 Ancillary Impacts of an MDA Program

By reducing infection rates across households, the MDA program also results in a small ($< 0.1\%$) increase in the supply of effective labor, which occurs because a lower infection rate means that one unit of labor time is now able to produce more and is thus more effective, all else equal.

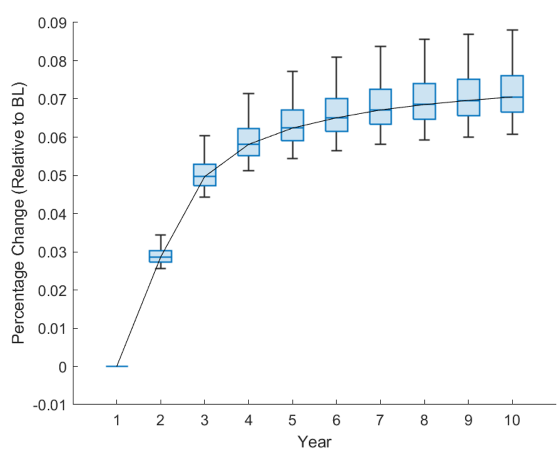
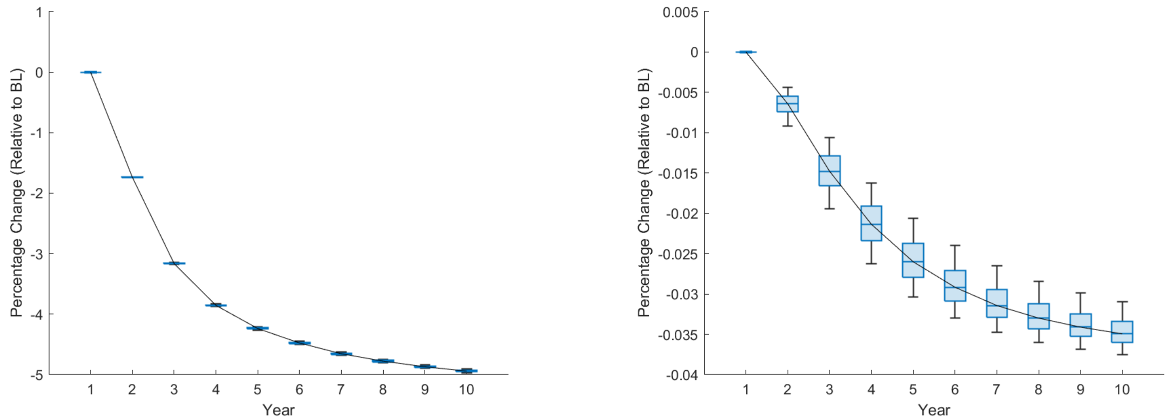


Figure 3.19: Percentage Changes in Effective Labor Supply from MDA Shock

While small, the increase in the supply of effective labor translates into a small ($< 0.1\%$) increase in pressure on the fish stock, which leads to a decline in the fish stock over time.

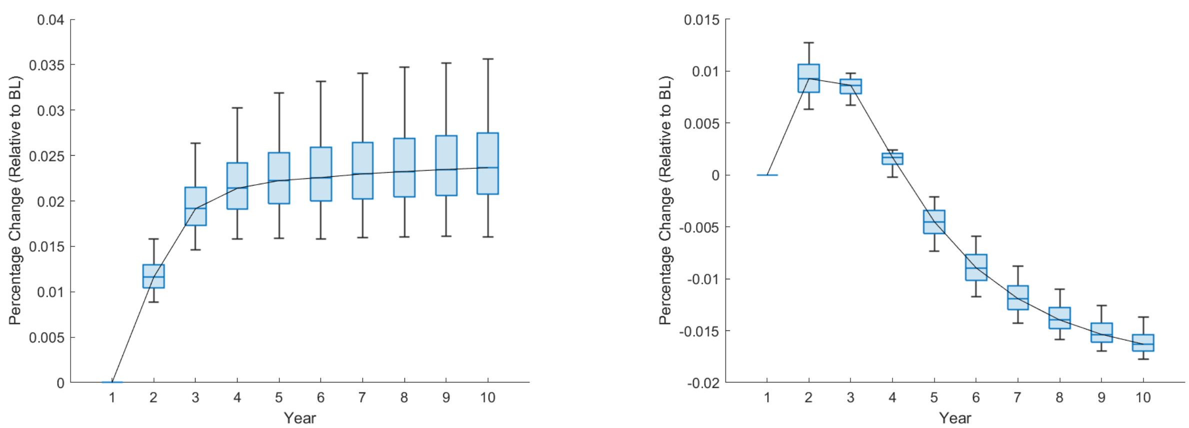
The decline in the fish stock increases search costs, pushing labor out of the fishing sector into other sectors in which its economic returns are higher. As labor leaves the fishing sector, fishing labor time declines.



(a) Fishing Labor Time (b) Fish Stock

Figure 3.20: Percentage Changes in Fishing Labor Time and Fish Stock Levels from MDA Shock

The decline in fishing labor time also reflects a decline in exposure time. The decline in exposure time is an ancillary benefit of the MDA program that contributes to the overall decline in household infection rates.



(a) Aggregate Output (b) Fishing Sector Output

Figure 3.21: Percentage Changes in Aggregate Output and Fishing Sector Output from MDA Shock

In addition to reducing household infection rates, the MDA program produces ancillary benefits for the local economy as well as costs for the ecosystem. For the local economy, the MDA program yields a (small) increase in aggregate output (Figure 3.21a) that occurs because the additional effective labor leads to higher output and higher household incomes, which has a ripple effect throughout the local economy. The increase in aggregate output is driven by growth in all sectors of the economy, with the sole exception of the fishing sector. The decline in fishing output is a result of the decline in fishing labor time. However, the increase in effective labor translates into an increase in fishing effort and consequently a small decline in the fish stock (see Figure 3.20), which is a knock on effect of the MDA program for the ecosystem and the stock of fish.

3.6 Policy Interactions

So far, we have seen how policies focusing on one domain often produce paradoxical effects in other domains, and that these effects may either mitigate or exacerbate outcomes in the ecological and health domains. I now consider how ancillary consequences may change when policy interventions occur concurrently. Importantly, I assume that two policies occur at the same time with no coordination between the implementing agencies. In other words, I am not considering a central planner designing the efficient or cost-effective combination of policies. While this could be an interesting theoretical exercise, it is unlikely to be applicable to the empirical setting in Uganda. I consider the implementation of an MDA program concurrent with the FMP shock and (separately) the TFP shock introduced above.

3.6.1 FMP-MDA Policy interactions

The objectives of the FMP and MDA policies are, respectively, to reduce current fishing effort, which reduces pressure on the fish stock and thus increases returns for future fishing effort, and to reduce household infection rates for Schisto. I model the concurrent implementation of the two policies using the same methods introduced above. Specifically, I model the FMP policy shock by introducing a 25% reduction in fishing capital in the first year and keeping it in place over the study period. I model the MPA program shock with an annual reduction of 19.3% in household infection rates, beginning in the first year (see Appendix 3.A.

Although the FMP shock results in additional fishing labor time—and consequently an increase in exposure time—by the end of the study period, the concurrent implementation of the FMP and MDA shocks results in a large decline in the value of R_0 over the study period. This decline occurs because the effect of the MDA program—an effective increase in the mortality rate of the parasite in the human host—is significantly larger than the effects of increased exposure time. While the recovery of the fish stock resulting from the

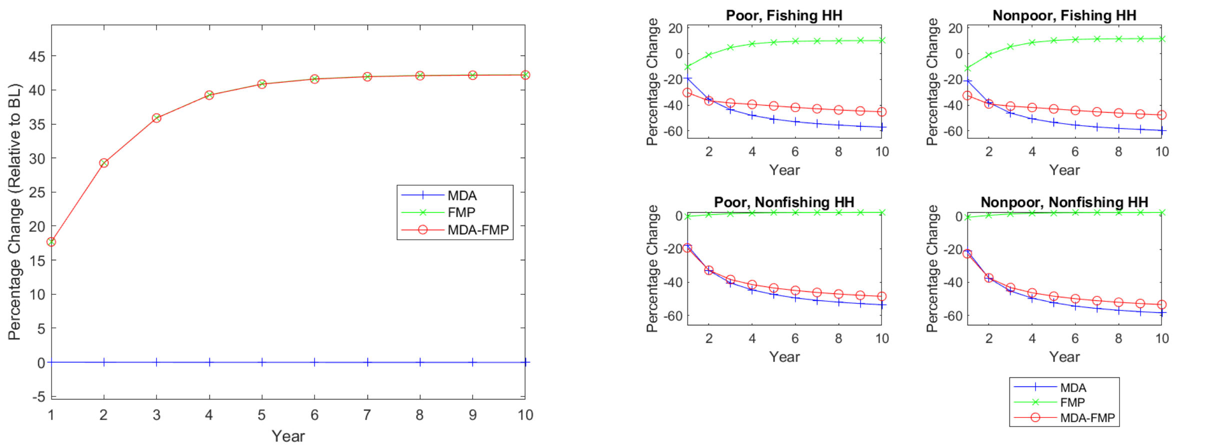
Table 3.4: Qualitative representation of changes in R_0, fish stock, and aggregate output across FMP, MDA, and concurrent FMP-MDA policy shocks.

Outcome	Policy Shock		
	FMP	MDA	FMP-MDA
R_0	↓ ↑	↓	↓
Fish Stock	↑	⇣	↑
Aggregate Output	↓ ↑	⇡	↓ ↑

Notes: Magnitude of change is indicated by thickness of the arrow. The sign of change is indicated by the direction of arrow. Dashed arrow indicates direction of change with negligible magnitude. Multiple arrows indicate a change of sign between years 1 and 10 and should be read left to right.

FMP shock is not meaningfully reduced by concurrent implementation of the two policies, the MDA shock does slightly attenuate the recovery of the fish stock. This result occurs because the labor employed in the fishing sector becomes more productive as a result of treatment for the disease, producing a (slight) increase in pressure on the fish stock. Even though the MDA program has a relatively minor effect on aggregate output as a result of the increase in labor productivity, the two policies are complementary. In summary, the concurrent implementation of the two policies produces positive results for all three aggregate measures.

There is no meaningful difference in fish stock outcomes between the FMP shock and the FMP-MDA shock (Figure 3.22a), which is consistent with the very small change in the fish stock resulting from the MDA shock (see Figure 3.20b). As a result of the FMP-MDA policies acting concurrently, median infection rates decline in year 1 by 30.2% for poor fishing households and 32.5% for nonpoor fishing households. Drawing from the results for the individual policy shocks (see Figures 3.13 and 3.17), we can surmise that approximately



(a) Fish Stock

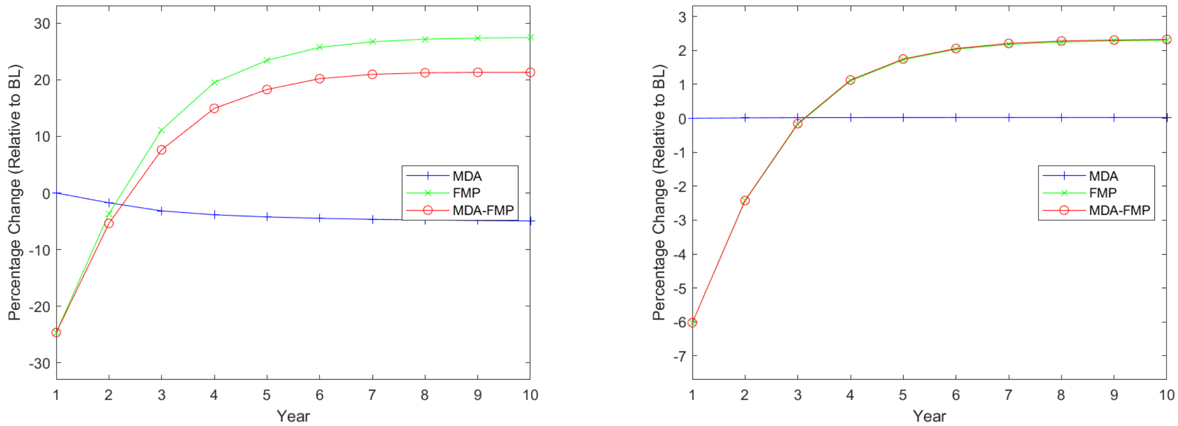
(b) Household Infection Rates

Figure 3.22: Percentage Changes (Relative to Baseline) in Fish Stock Levels and Household Infection Rates from FMP-MDA Policy Interaction

two-thirds of this initial decline is due to the MDA component of the combined policy and the remaining one-third is attributable to the FMP component.

The mechanisms driving these results are as follows. The fish stock starts to recover shortly after initial policy implementation, slowly drawing effort back into the sector. However, by the fourth year after policy implementation, the additional gains from the combined shock–as measured by the larger short-term decline in infection rates for fishing households–are lost. Even though infection rates continue to decline, the recovery of the fish stock draws enough effort back into the fishing sector to keep infection rates for all households, and in particular fishing households, above the levels observed in the MDA-only shock.

The share of the initial decline in infection rates that is attributable to the FMP component occurs because the policy-induced restriction on capital initially pushes labor out of the fishing sector, resulting in an initial decline in exposure time. The recovery of the fish stock over time draws effort back into the fishing sector, resulting in a net increase in fishing labor time by the end of the study period. In the FMP shock discussion above, this was noted as an important ancillary consequence of the policy because this increase in fishing labor time resulted in an increase in infection rates for fishing households. We contrast that outcome



(a) Fishing Labor Time

(b) Aggregate Output

Figure 3.23: Percentage Changes in Fishing Labor Time and Aggregate Output from FMP-MDA Policy Interaction

with the result from the FMP-MDA shock that infection rates for all households, including fishing households, drop initially and continue to decline over the study period (Figure 3.22b). We conclude that an important feature of MDA programs may be the capacity for offsetting negative secondary effects of policies such as the FMP shock modeled above.

3.6.2 TFP-MDA Policy interactions

The objectives of the TFP and MDA policies are, respectively, to increase yields in the oil palm sector and to reduce household infection rates for Schisto. I model the TFP policy shock by increasing the value of the shift parameter in the oil palm production function by 10% each year, beginning in the first year. I model the MPA program shock with an annual reduction of 19.3% in household infection rates, beginning in the first year (see Appendix 3.A).

Although the TFP shock targets the oil palm sector, the ripple effects of the shock throughout the local economy result in an increase in aggregate output. The MDA program produces a small gain in aggregate output resulting from the increase in labor productivity. Furthermore, R_0 declines due to the increase in aggregate output, showing that when implemented

Table 3.5: Qualitative representation of changes in R_0, fish stock, and aggregate output across TFP, MDA, and concurrent TFP-MDA policy shocks.

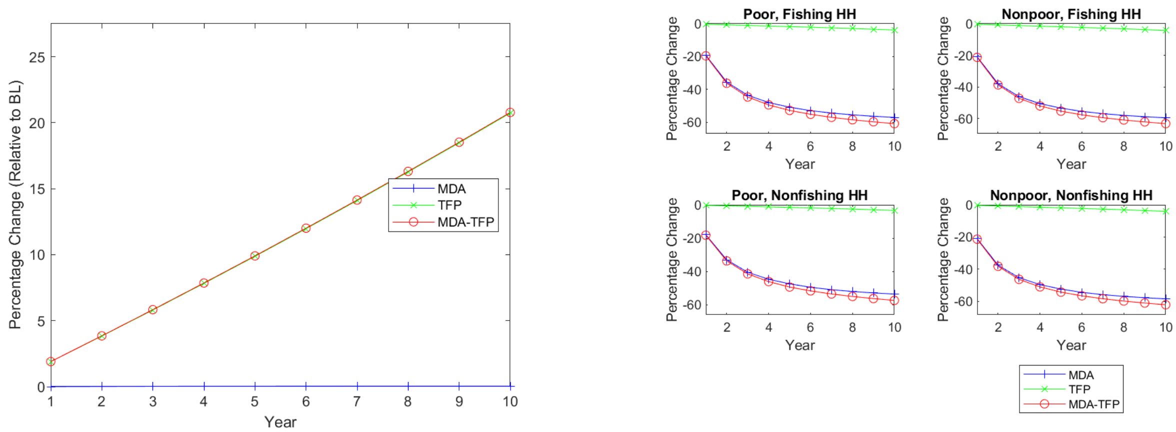
Outcome	Policy Shock		
	TFP	MDA	TFP-MDA
R_0	↓	**↓**	**↓**
Fish Stock	⇡	⇣	⇡
Aggregate Output	↑	⇡	↑

Notes: Magnitude of change is indicated by thickness of the arrow. The sign of change is indicated by the direction of arrow. Dashed arrow indicates direction of change with negligible magnitude. Multiple arrows indicate a change of sign between years 1 and 10 and should be read left to right.

concurrently, the TFP shock and the MDA program have complementary effects for aggregate output and R_0. The TFP shock produces a small increase in the fish stock due to a decrease in pressure on the stock as labor time is shifted out of the sector and into oil palm (see Figure 3.4a). However, pressure on the fish stock increases because the labor that producers employ becomes more effective as a result of the MDA program. Even though the two policies have opposing effects on the fish stock, the concurrent implementation of the two shocks produces a small net increase in the fish stock.

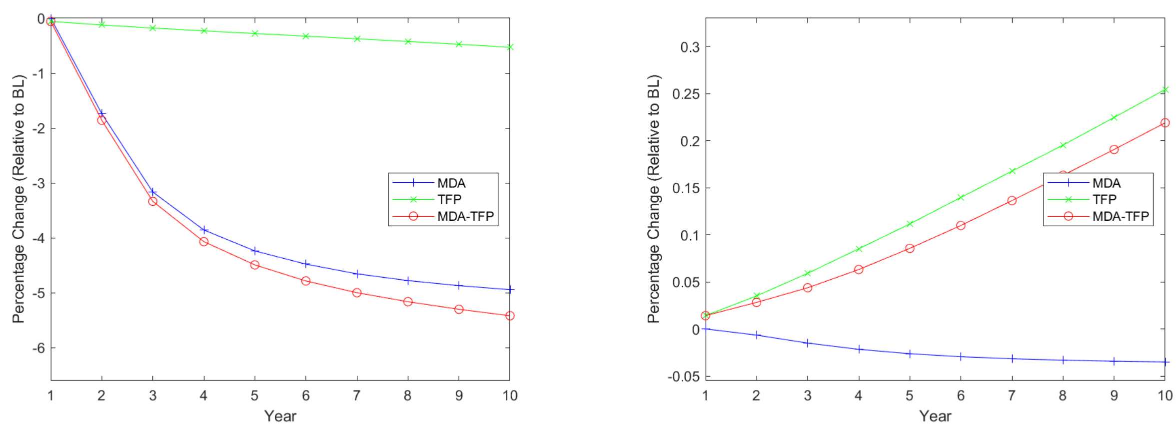
Because of the negligible effect that the MDA program has on the oil palm sector, there is no meaningful difference in results between the TFP shock and the TFP-MDA shock depicted in Figure 3.24a. The MDA program contributes the majority of the decline in infection rates observed in Figure 3.24b. The TFP shock contributes to the remaining portion of the overall decline due to the knock-on effect of drawing labor from the fishing sector.

Both policy shocks contribute to the overall decline in fishing labor time that results from the TFP-MDA shock (Figure 3.25a). The (small) decline in the fish stock that results from



(a) Oil Palm Sector Output (b) Household Infection Rates

Figure 3.24: Percentage Changes (Relative to BL) in Oil Palm Sector Output and Household Infection Rates from TFP-MDA Policy Interaction



(a) Fishing Labor Time (b) Fish stock

Figure 3.25: Percentage Changes in Fishing Labor Time and Fish Stock from TFP-MDA Policy Interaction

the MDA program is offset by the increase that results from the TFP shock, yielding a net increase in the fish stock from the TFP-MDA shock. The increase is small, at less than 1% by the end of the study period, but the direction of the change is meaningful because it demonstrates the (small in magnitude) ancillary consequences for the ecosystem that are produced by both the TFP-MDA shock.

3.7 Discussion

A policy shock in one of the three domains—economic, public health, and biological—has knock on effects for the other domains. In addition to increasing oil palm output and raising income from oil palm production for all four households in the local economy, the ancillary benefits of the TFP shock include an increase in household income from all other sectors, a reduction in household infection rates, a (small) increase of the fish stock. Although the FMP shock achieves the policymakers' objective of increasing the size of the fish stock by regulating fishing effort, this regulation does not limit the return of fishing labor time to the sector in response to the recovery of the fish stock. Consequently, one knock on effect of the FMP shock is a net increase in exposure time to the disease over the study period, which translates to a net increase in infection rates for fishing households. The MDA program satisfies the objective of reducing infection rates for all four households, which has the ancillary benefit of increasing the supply of effective labor in the local economy, since each unit of labor time is able to produce more as a result of the reduction in infection rates. However, the increase in effective labor translates to an increase in fishing effort, which results in a (small) reduction in the fish stock–an ancillary cost of the MDA program.

The combination of the MDA and FMP shocks demonstrates a trade-off between fisheries management policy goals and public health goals. The combined shock results in larger short-term reductions in infection rates compared to those observed in the sector-based policy interventions. However, the additional gains (as measured by infection rate reductions) do not persist over the study period; fishing labor time is drawn back into the sector by the recovery of the fish stock, and by the end of the study period household infection rates are higher than those observed in the MDA-only intervention. By including the FMP shock, the objective of allowing the fish stock to recover by regulating fishing effort is achieved. However, the cost of including this shock is higher household infection rates, which is contrary to the objective of the MDA program.

Table 3.6: Qualitative representation of changes in R_0, fish stock, and aggregate output across policy shocks.

Outcome	Policy Shock				
	TFP	FMP	MDA	FMP-MDA	TFP-MDA
R_0	↓	↓ ↑	**↓**	**↓**	**↓**
Fish Stock	⇡	**↑**	⇣	**↑**	⇡
Aggregate Output	**↑**	**↓** ↑	⇡	**↓** ↑	**↑**

Notes: Magnitude of change is indicated by thickness of the arrow. The sign of change is indicated by the direction of arrow. Dashed arrow indicates direction of change with negligible magnitude. Multiple arrows indicate a change of sign between years 1 and 10 and should be read left to right.

Furthermore, the TFP and FMP shocks considered in these simulations have limited potential for reducing the prevalence of the disease Schistosomiasis. It may be that without coordination with other types of mitigation efforts, including MDA treatment, policy shocks that affect the economy may also have similar, limited potential in reducing the prevalence of the disease.

For the TFP and FMP shocks, it could be that the size of the shock will determine the magnitude of any observed changes in disease prevalence. For example, a doubling of the increase in Oil Palm TFP considered above *may* result in a decline in the R_0 of approximately 10% by the end of the study period. However, given that the median baseline value of R_0 is 2.76, a decline of 10% is far from the required minimum decline of 64% needed to eliminate the disease by destabilizing the endemic equilibrium. Additionally, larger increases in Oil Palm TFP may not be realistic. It *might* be that a thirteen-fold increase in the size of the Oil Palm TFP shock could result in stabilization of the disease-free equilibrium. However, such an annual increase of 13% in Oil Palm TFP translates to a 340% increase in Oil Palm

Table 3.7: Representation of changes to household infection rates across policy shocks.

Outcome	Policy Shock				
	TFP	FMP	MDA	FMP-MDA	TFP-MDA
Poor, Fish	↓	↓ ↑	↓	↓	↓
Nonpoor, Fish	↓	↓ ↑	↓	↓	↓
Poor, Nonfish	↓	↓ ⇡	↓	↓	↓
Nonpoor, Nonfish	↓	↓ ⇡	↓	↓	↓

Notes: Magnitude of change is indicated by thickness of the arrow. The sign of change is indicated by the direction of arrow. Dashed arrow indicates direction of change with negligible magnitude. Multiple arrows indicate a change of sign between years 1 and 10 and should be read left to right.

TFP over ten years!

The results for the FMP shock suggest that meaningful trade-offs exist between achieving goals prioritized by different policymakers. As a result of the FMP shock, the fish stock grows by approximately 55% by the end of the study period, indicating that at least partial progress toward the goal of reducing overfishing can be met with such a policy shock. However, the ancillary consequences of this type of policy for the health status of fishing households are notable–because of the resurgence of the fish stock, effort is drawn back into the sector. As effort increases, so does exposure time to the disease, creating an unintended, negative consequence of the policy. As shown above, infection rates rose for fishing households over the study period, reinforcing the conditions that foster disease-based poverty traps.

Table 3.8: Representation of changes to sector output across policy shocks.

Outcome	Policy Shock				
	TFP	FMP	MDA	FMP-MDA	TFP-MDA
Crops	↑	⇡	⇡	⇡	↑
Livestock	↑	⬇ ↑	⇡	⬇ ↑	↑
Fishing	⇡	↓ ↑	⇣	↓ ↑	⇡
Oil Palm	⬆	⇡ ⇣	⇡	⇡ —	⬆
Retail	↑	↓	⇡	⬇	↑
Services	↑	↓ ↑	⇡	⬇ ↑	↑

Notes: Magnitude of change is indicated by thickness of the arrow. Sign of change is indicated by direction of the arrow. Dashed arrow indicates direction of change with negligible magnitude. Multiple arrows indicate a change of sign during the study period and should be read left to right.

Bibliography

Anderson, Jock R. and Gershon Feder (2007). "Chapter 44 Agricultural Extension". In: *Handbook of Agricultural Economics*. Elsevier, pp. 2343–2378. DOI: 10.1016/s1574-0072(06)03044-1. URL: https://doi.org/10.1016/s1574-0072(06)03044-1.

Castonguay, François M., Susanne H. Sokolow, Giulio A. De Leo, and James N. Sanchirico (2020). "Cost-Effectiveness of Combining Drug and Environmental Treatments for Environmentally Transmitted Diseases". In: *Proceedings of the Royal Society B: Biological Sciences* 287.1933, p. 20200966. DOI: 10.1098/rspb.2020.0966.

Filipski, Mateusz and Ben Belton (Oct. 2018). "Give a Man a Fishpond: Modeling the Impacts of Aquaculture in the Rural Economy". In: *World Development* 110, pp. 205–223. DOI: 10.1016/j.worlddev.2018.05.023. URL: https://doi.org/10.1016/j.worlddev.2018.05.023.

Gilliland, Ted E., James N. Sanchirico, and J. Edward Taylor (2019). "An Integrated Bioeconomic Local Economy-wide Assessment of the Environmental Impacts of Poverty Programs". In: *Proceedings of the National Academy of Sciences* 116.14, pp. 6737–6742. DOI: 10.1073/pnas.1816093116. eprint: https://www.pnas.org/content/116/14/6737.full.pdf. URL: https://www.pnas.org/content/116/14/6737.

– (Apr. 2022). "A Bioeconomic Local General Equilibrium Assessment of Distributional Consequences of Small-Scale Fisheries Reform in Developing Countries". In: *Marine Resource Economics* 37.2, pp. 111–134. DOI: 10.1086/718379. URL: https://doi.org/10.1086/718379.

Halstead, Neal T., Christopher M. Hoover, Arathi Arakala, David J. Civitello, Giulio A. De Leo, Manoj Gambhir, Steve A. Johnson, Nicolas Jouanard, Kristin A. Loerns, Taegan A. Mcmahon, and et al. (2018). "Agrochemicals Increase Risk of Human Schistosomiasis by Supporting Higher Densities of Intermediate Hosts". In: *Nature Communications* 9.1. DOI: 10.1038/s41467-018-03189-w.

Hasnah, Euan Fleming, and Tim Coelli (Jan. 2004). "Assessing the Performance of a Nucleus Estate and Smallholder Scheme for Oil Palm Production in West Sumatra: A Stochastic Frontier Analysis". In: *Agricultural Systems* 79.1, pp. 17–30. DOI: 10.1016/s0308-521x(03)00043-x. URL: https://doi.org/10.1016/s0308-521x(03)00043-x.

Inobaya, M. T., R. M. Olveda, T. N. Chau, D. U. Olveda, and A. G. Ross (2014). "Prevention and Control of Schistosomiasis: A Current Perspective". In: *Research and Reports in Tropical Medicine* 5.1722, pp. 65–75. DOI: doi.org/10.2147/RRTM.S44274.

Jelsma, Idsert, Maja Slingerland, Ken E. Giller, and Jos Bijman (2017). "Collective Action in a Smallholder Oil Palm Production System in Indonesia: The Key to Sustainable and

Inclusive Smallholder Palm Oil?" In: *Journal of Rural Studies* 54, pp. 198–210. ISSN: 0743-0167. DOI: 10.1016/j.jrurstud.2017.06.005. URL: https://www.sciencedirect.com/science/article/pii/S0743016716303941.

Khatun, Kaysara, Victoria Alice Maguire-Rajpaul, Elizabeth Asiedua Asante, and Constance L. McDermott (Mar. 2020). "From Agroforestry to Agroindustry: Smallholder Access to Benefits From Oil Palm in Ghana and the Implications for Sustainability Certification". In: *Frontiers in Sustainable Food Systems* 4. DOI: 10.3389/fsufs.2020.00029. URL: https://doi.org/10.3389/fsufs.2020.00029.

King, Charles H., Nupur Kittur, Sue Binder, Carl H. Campbell, Eliézer K. N'Goran, Aboulaye Meite, Jürg Utzinger, Annette Olsen, Pascal Magnussen, Safari Kinung'hi, Alan Fenwick, Anna E. Phillips, Pedro H. Gazzinelli-Guimaraes, Neerav Dhanani, Josefo Ferro, Diana M. S. Karanja, Pauline N. M. Mwinzi, Susan P. Montgomery, Ryan E. Wiegand, William Evan Secor, Amina A. Hamidou, Amadou Garba, and Daniel G. Colley (July 2020). "Impact of Different Mass Drug Administration Strategies for Gaining and Sustaining Control of Schistosoma mansoni and Schistosoma haematobium Infection in Africa". In: *The American Journal of Tropical Medicine and Hygiene* 103.1_Suppl, pp. 14–23. DOI: 10.4269/ajtmh.19-0829. URL: https://doi.org/10.4269/ajtmh.19-0829.

King, Charles H., Robert F. Sturrock, H. Curtis Kariuki, and Joseph Hamburger (Dec. 2006). "Transmission control for schistosomiasis – why it matters now". In: *Trends in Parasitology* 22.12, pp. 575–582. ISSN: 1471-4922. DOI: 10.1016/j.pt.2006.09.006. URL: http://dx.doi.org/10.1016/j.pt.2006.09.006.

Kolding, Jeppe, Medard Modesta, Oliva Mkumbo, and Paul van Zweiten (2014). *Inland Fisheries Evolution and Management: Case Studies from Four Continents*. Tech. rep. Food and Agriculture Organization.

Lindsay, Amanda R., James N. Sanchirico, Ted E. Gilliland, Rohani Ambo-Rappe, J. Edward Taylor, Nils C. Krueck, and Peter J. Mumby (2020). "Evaluating Sustainable Development Policies in Rural Coastal Economies". In: *Proceedings of the National Academy of Sciences* 117.52, pp. 33170–33176. ISSN: 0027-8424. DOI: 10.1073/pnas.2017835117. URL: https://www.pnas.org/content/117/52/33170.

Lo, Nathan C., David Gurarie, Nara Yoon, Jean T. Coulibaly, Eran Bendavid, Jason R. Andrews, and Charles H. King (Jan. 2018). "Impact and Cost-Effectiveness of Snail Control to Achieve Disease Control Targets for Schistosomiasis". In: *Proceedings of the National Academy of Sciences* 115.4. DOI: 10.1073/pnas.1708729114. URL: https://doi.org/10.1073/pnas.1708729114.

Manning, Dale T., J. Edward Taylor, and James E. Wilen (Jan. 2018). "General Equilibrium Tragedy of the Commons". In: *Environmental and Resource Economics* 69.1, pp. 75–101. ISSN: 1573-1502. DOI: 10.1007/s10640-016-0066-7. URL: https://doi.org/10.1007/s10640-016-0066-7.

Masiga, M., S. Khauka, and M. Nabatanzi (2019). *Future Economic Trajectories for Oil Palm in Buvuma and Kalangala Districts*. Tech. rep. Ecological Trends Alliance. URL: https://nru.uncst.go.ug/xmlui/handle/123456789/1029.

Monzon, Juan Pablo, Ya Li Lim, Fatima A. Tenorio, Rana Farrasati, Iput Pradiko, Hendra Sugianto, Christopher R. Donough, Juan I. Rattalino Edreira, Suroso Rahutomo, Fahmuddin Agus, Maja A. Slingerland, Mink Zijlstra, Shofia Saleh, Fakhrizal Nashr, Denni Nurdwiansyah, Nadib Ulfaria, Nurul L. Winarni, Nurbaya Zulhakim, and Patricio Grassini (2023). “Agronomy Explains Large Yield Gaps in Smallholder Oil Palm Fields”. In: *Agricultural Systems* 210, p. 103689. ISSN: 0308-521X. DOI: https://doi.org/10.1016/j.agsy.2023.103689. URL: https://www.sciencedirect.com/science/article/pii/S0308521X2300094X.

Nsamba-Gayiiya, Eddie and Herbert Kamusiime (July 2015). *Brokering Development: Enabling Factors for Public-Private-Producer Partnerships in Agricultural Value Chains. Summary of Uganda Case study.* URL: https://opendocs.ids.ac.uk/opendocs/handle/20.500.12413/6460?show=full.

Nyamweya, C. S., H. M. Nyaboke, C. M. Aura, K. N. Momanyi, E. Mlaponi, C. O. Odoli, and J. M. Njiru (Sept. 2022). “Lake Victoria’s Bounty: A Case for Riparian Countries’ Blue Economic Investment”. In: *Frontiers in Environmental Science* 10. DOI: 10.3389/fenvs.2022.952654. URL: https://doi.org/10.3389/fenvs.2022.952654.

Purcell, Steven W. and Robert S. Pomeroy (June 2015). “Driving Small-Scale Fisheries in Developing Countries”. In: *Frontiers in Marine Science* 2. DOI: 10.3389/fmars.2015.00044. URL: https://doi.org/10.3389/fmars.2015.00044.

Secretariat, Lake Victoria Fisheries Organization (LVFO) (2016). *Fisheries Management Plan III (FMP III) for Lake Victoria Fisheries 2016-2020.* Tech. rep. Lake Victoria Fisheries Organization.

Standley, Claire J., Moses Adriko, Moses Arinaitwe, Aaron Atuhaire, Francis Kazibwe, Alan Fenwick, Narcis B. Kabatereine, and J. Russell Stothard (2010). “Epidemiology and Control of Intestinal Schistosomiasis on the Sesse Islands, Uganda: Integrating Malacology and Parasitology to Tailor Local Treatment Recommendations”. In: *Parasites & Vectors* 3.1, p. 64. DOI: 10.1186/1756-3305-3-64.

Standley, Claire J., Moses Adriko, Fred Besigye, Narcis B. Kabatereine, and Russell J. Stothard (2011). “Confirmed Local Endemicity and Putative High Transmission of *Schistosoma mansoni* in the Sesse Islands, Lake Victoria, Uganda”. In: *Parasites & Vectors* 4.1, p. 29. DOI: 10.1186/1756-3305-4-29.

Taylor, J. Edward and Mateusz J. Filipski, eds. (2014). *Beyond Experiments in Development Economics: Local Economy-Wide Impact Evaluation.* Oxford: Oxford University Press.

Taylor, J. Edward, Mateusz J. Filipski, Mohamad Alloush, Anubhab Gupta, Ruben Irvin Rojas Valdes, and Ernesto Gonzalez-Estrada (June 2016). “Economic Impact of Refugees”. en. In: *Proc Natl Acad Sci U S A* 113.27, pp. 7449–7453.

Taylor, J. Edward, Edward Whitney, and Heng Zhu (Oct. 2019). “Local-Economy Impacts of Cash Crop Promotion”. In: *Food and Agricultural Organization, United Nations* 40 IFAD Research Series, pp. 1–34. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3465509.

Tukahebwa, Edridah M., Pascal Magnussen, Henry Madsen, Narcis B. Kabatereine, Fred Nuwaha, Shona Wilson, and Birgitte J. Vennervald (July 2013). “A Very High Infection Intensity of Schistosoma mansoni in a Ugandan Lake Victoria Fishing Community Is Required for Association with Highly Prevalent Organ Related Morbidity”. In: *PLOS Neglected Tropical Diseases* 7.7, pp. 1–8. DOI: 10.1371/journal.pntd.0002268. URL: https://doi.org/10.1371/journal.pntd.0002268.

Witte, Frans, Tijs Goldschmidt, Jan Wanink, Martien van Oijen, Kees Goudswaard, Els Witte-Maas, and Niels Bouton (May 1992). “The Destruction of an Endemic Species Flock: Quantitative Data on the Decline of the Haplochromine Cichlids of Lake Victoria”.

In: *Environmental Biology of Fishes* 34.1, pp. 1–28. ISSN: 1573-5133. DOI: 10.1007/BF00004782. URL: https://doi.org/10.1007/BF00004782.

3.A Parameterizing the MDA shock

To model the impact of an MDA program targeted at reducing Schisto prevalence, I introduce the shock parameter γ_{mda} into my Epi system of equations:

$$I_{h,t+1} - I_{h,t} = \beta_t \tau_{h,t} \epsilon_h Y_t (1 - I_{h,t}) - \gamma_t (1 + \gamma_{mda}) I_{h,t} \tag{3.3}$$

$$Y_{t+1} - Y_t = \beta_t (1 - Y_t) \sum_{h=1}^{H} g_h \tau_{h,t} \epsilon_h I_{h,t} - \mu Y_t \tag{3.4}$$

The term $\gamma_t(1 + \gamma_{mda})$ represents the rate of transition out of the infection classification for the subpopulation group. I model γ_t as increasing in aggregate output with the following minimum and maximum values:

$$\gamma_{min} = 5.5 \times 10^{-4} \tag{3.5}$$

$$\gamma_{max} = 5.5 \times 10^{-3} \tag{3.6}$$

I assign a value for γ_{mda} that produces a decline in infection rates that is consistent with prior literature. I first identify a value for annual reduction rates in Schisto infection that can result from community-wide MDA programs in communities similar to the one under study here. King, Kittur, et al. (2020) studies the impact of annual community-based treatment for Schisto on infection rates in three countries: Kenya, Mozambique, and Tanzania. Evaluating changes in prevalence rates between year 1 and year 5 after program implementation, they find a decline in prevalence of approximately 74% (Kenya), 36% (Tanzania), and 55% (Mozambique). These changes are equivalent to annual reduction rates of 29% (Kenya), 11% (Tanzania), and 18% (Mozambique), and the simple average of these rates is 19.3%.

To solve for γ_{mda}, I convert the left side of Equation(3.3) to a percentage change by dividing both sides by I_h and set the left side of the equation equal 0.193, which is the annual reduction rate identified above. I solve for the desired value of γ_{mda} using baseline values of the Epi state variables I_h and Y and the parameters β, γ, and τ_h. Since the MDA treatment only targets the human population, I assume no changes in Y over the study period, which is consistent with results shown in Figure 7b from Castonguay et al. (2020). I calculate a value of γ_{mda} equal to 0.295 that I use to model the MDA policy shock in this chapter.

Chapter 4

A Disease-free Counterfactual

4.1 Introduction

All else equal, healthier economies grow faster. Improvements in health can lead to increases in life expectancy, which in turn can result in higher rates of savings (Bloom et al., 2007), reduced healthcare-related expenditures (thereby freeing up scarce funds), and increased investment in human and physical capital (Cervellati and Sunde, 2013). When health outcomes improve, labor force participation rates may increase (Novignon, Nonvignon, and Arthur, 2015), or the economy may experience growth in the size of the working-age population (Mason, Lee, and Jiang, 2016). Improvements in the health of the labor force can also contribute to less workplace absenteeism and higher labor productivity (Strauss and Thomas, 1998).

In developing countries such as Uganda, each of these factors are important because of the country's potential to maximize gains from their "demographic dividend," a period of time in which the size of the working-age population is increasing faster than the size of the non-working age population (Lee and Mason, 2006). For Uganda, this window of time is anticipated to begin by 2030 and is expected to last approximately four decades (Matovu et al., 2018). During this period, a healthier working population will be able to produce more, resulting in higher household incomes, aggregate output, and economic growth.

I use the Epi-Bio-LEWIE (EBL) model developed in Chapter 2 to investigate the impact of Schistosomiasis (Shisto) on economic growth. Specifically, I compare changes in key outcomes across two versions of the EBL model: the observed local economy and a disease-free counterfactual, which I describe in the next section. I simulate exogenous growth in the economy in the form of annual changes in the total factor productivity of the oil palm sector. I use aggregate output, household incomes, labor allocation across sectors, and fish stock levels as primary outcomes. I compare results from the two models across high ($\eta = 100$) and low ($\eta = 1$) levels of labor supply elasticity. The hypothesis is that the elasticity of the labor supply affects the impact that Schisto has on economic growth.

4.2 Methods

I obtain the baseline values of the EBL model in a process in which I assume that each of the three component models—Epi, Bio, and LEWIE—is in equilibrium and that equilibrium exists across the three models. Absent an exogenous shock to the model, the baseline values of the model do not change over time. This allows for the baseline model to be used as a counterfactual for comparison with results obtained by introducing a shock to the model, as in Chapter 3 and in previous studies (e.g., Taylor and Filipski, 2014).

The results presented in this chapter are obtained using a different counterfactual. Specifically, I construct a disease-free counterfactual of the local economy by reducing the impact that Schisto has on labor time to zero in the first year. To do this, I rely on the equation

$$E_h = L_h(1 - I_h\alpha) \tag{4.1}$$

which states that the household supply of effective labor, E_h, depends on its supply of labor time, L_h, its infection rate I_h, and α, which is the impact that the disease has on a unit of labor time. Mechanically, reducing α to zero produces a version of the local economy in which the supply of effective labor is equal to the supply of labor time in the first year and over the 10-year study period. Conceptually, this change results in a disease-free version of the human-natural environment that is comparable to previous Bio-LEWIE studies (e.g., Lindsay et al., 2020).

To investigate how the labor market structure matters, I compare results across two scenarios in which I vary the elasticity of the labor supply, denoted as η below. In the first scenario, the labor supply is highly elastic ($\eta = 100$) and the local economy model is in the world of Lewis (1954). The wage paid to effective labor is near subsistence wages, unemployment is high, and surplus labor is abundant. In the second scenario, the labor supply is inelastic ($\eta = 1$). Wages exceed subsistence levels and respond to changes in quantities of labor supplied and demanded. Frictions in the labor market may stem from a dearth of formal sector employment, which is characteristic of contemporary Uganda (Guloba et al., 2021).

I model exogenous growth in the local economy by increasing Oil Palm total factor productivity (TFP) by 3% each year. This level of growth represents successful efforts to close the productivity gap between contracted small household producers and the central estate on the island, which was reported to be approximately 33% (i.e., average yields for smallholder households were approximately 33% less than those for the central estate).[1] One common method for improving yields among smallholder producers is by way of agricultural extension services (Anderson and Feder, 2007). I also consider how the size of the TFP shock affects changes in outcomes by simulating smaller annual increases in Oil Palm TFP.

[1]As discussed in meetings held in September 2017 with the management team for the central estate in Kalangala District. While we were unable to independently verify this claim, it is qualitatively consistent with productivity gaps observed in other similarly structured (i.e., central estate with smallholder producers) oil-palm producing areas (e.g., Hasnah, Fleming, and Coelli, 2004).

4.3 Results

The effect that Schisto has on economic growth depends on the elasticity of labor supply. When the labor supply is highly elastic, there is little difference in outcomes between the DF and observed economies. In contrast, when the labor supply is inelastic, we observe differences across most outcomes.

4.3.1 Aggregate Output

We first observe that, all else equal, aggregate output in the economy with a highly elastic labor supply grows faster than the economy with a unit-elastic labor supply. This result is not surprising, since the increase in demand for labor resulting from economic growth can more readily be met by an increase in the supply of labor when the labor supply is highly elastic. Conversely, when the labor supply is inelastic, an increase in the demand for labor will create upward pressure on wages, since there is limited capacity for the labor supply to grow.

Table 4.1: Percentage Changes (Relative to Baseline) in Aggregate Output for DF Counterfactual and Observed Economy

Labor Elasticity	Timespan	DF	Observed Economy	Difference (%)
$\eta = 1$	1st year	1.81	1.81	0.00
	10th year	25.85	23.76	8.10
$\eta = 100$	1st year	2.58	2.58	0.00
	10th year	33.26	33.20	0.17

Notes: Difference is calculated as shift from DF to observed economy.

The first-year percentage increase aggregate output is the same for the DF and observed economies, supporting the claim that the DF scenario serves as a valid counterfactual for the observed economy. The minimal impact that Schisto has on economic growth when the labor supply is highly elastic is observed in the negligible difference in aggregate output growth over the 10-year study period (0.1%) between the DF and observed economies. In contrast, when the labor supply is inelastic, the prevalence of Schisto manifests as a friction in the labor market and results in a reduction in aggregate output of 8.1% over the study period.

4.3.2 Wages and The Supply of Effective Labor

Within the DF and observed economies, wage growth over time is minimal when the labor supply is highly elastic, since the supply of effective labor can grow to meet the increase in demand that results from growth in the economy. Consequently, we observe only small level differences in changes in the highly elastic effective labor supply between the disease-free and observed economy.

Table 4.2: Percentage Changes (Relative to Baseline) over 10-Year Study Period in Wages and Effective Labor for DF Counterfactual and Observed Economy

Labor Elasticity	Outcome	DF	Observed Economy	Difference (%)
$\eta = 1$	Effective Labor	20.8	15.3	26.5
	Wages	10.7	14.3	-33.7
$\eta = 100$	Effective Labor	40.4	40.2	0.4
	Wages	0.3	0.3	-30.0

Notes: Difference is calculated as shift from DF to observed economy.

However, when the labor supply is inelastic, we observe lower levels of growth in the supply of effective labor for the DF and observed economies. This result is due to the fact that the supply of effective labor cannot easily adjust in response to changes in the quantity of labor demanded by producers when the labor supply is inelastic. Instead, wages must adjust in order for the labor market to reach equilibrium. Consequently, economic growth with a unit-elastic labor supply results in wages increasing by approximately 10.7% (DF) and 14.3% (observed economy) above baseline levels. Furthermore, when the labor supply is inelastic, the amount of labor supplied in the observed economy increases at a slower pace than the labor supply for the disease-free counterfactual.

4.3.3 Household Incomes

In section 4.3.1, we see that Schisto leads to a decline of 8.1% in aggregate output over the 10-year study period when the labor supply is inelastic. Disaggregating across household types, we observe that this decline in aggregate output manifests as a reduction in household income growth for all household types. Income growth for poor-nonfishing households is reduced by approximately 6.2%, from 43.5% to 40.7%. In contrast, income growth for both fishing household groups declines by (approximately) only 1.5%.

Table 4.3: Percentage Changes (Relative to Baseline) over 10-Year Study Period in Household Incomes for DF Counterfactual and Observed Economy

Labor Elasticity	Household	DF	Observed Economy	Difference (%)
$\eta = 1$	Poor, Fishing	23.9	23.5	1.8
	Nonpoor, Fishing	12.2	12.0	1.6
	Poor, Nonfishing	24.0	21.6	10.2
	Nonpoor, Nonfishing	14.9	13.8	8.0
$\eta = 100$	Poor, Fishing	28.0	27.9	0.4
	Nonpoor, Fishing	14.6	14.7	-0.8
	Poor, Nonfishing	30.7	30.1	1.9
	Nonpoor, Nonfishing	19.5	19.6	-0.7

Notes: Difference is calculated as shift from DF to observed economy.

The heterogeneous impact of Schisto across household incomes is a consequence of the degree to which each household participates in the Oil Palm sector. While all households participate the Oil Palm sector, Poor Nonfishing households generate a larger share of their total output from the Oil Palm sector compared to other households (see Appendix 4.A). Consequently, while a unit-elastic labor market results in all households in the observed scenario not producing as much oil palm as they do in the counterfactual scenario, the difference is starkest for Poor Nonfishing households.

4.3.4 Fish Stock

The exogenously driven growth in the oil palm sector of the local economy results in a recovery of the fish stock over the 10-year study period, a result that is robust to the elasticity of the labor supply or the presence of Schisto in the human population. A highly elastic labor supply results in more pressure on the fish stock relative to the unit-elastic labor supply. This difference stems from the fact that demand for labor can be readily be met when the labor supply is highly elastic, which results in larger fish harvests.

Figure 4.1: Percentage Changes (Relative to Baseline) over 10-Year Study Period in Fish Stock for DF Counterfactual and Observed Economy

Labor Elasticity	DF	Observed Economy	Difference (%)
$\eta = 1$	7.1	9.5	-34.8
$\eta = 100$	0.8	0.8	-7.1

Notes: Difference is calculated as shift from DF to observed economy.

However, Schisto reduces pressure on the fish stock because fishing labor is less productive, all else equal. Furthermore, when the labor supply is inelastic and thus less able to reallocate across sectors, the effect of the labor productivity loss from Schisto on the fish stock is magnified. Comparing across the DF and observed economies, the fish stock recovers by 34.8% more when $\eta = 1$, whereas the additional recovery of the fish stock is only 7.1% when the labor supply is highly elastic. This is consistent with results shown in Chapter 3 and supports the conclusion that disease prevalence may be unintentionally propping up fish stocks in Lake Victoria and elsewhere.

4.3.5 Are these results robust to the size of the TFP shock?

The results are based on a annual, exogenous increase of 3% in Oil Palm TFP. To investigate whether the heterogenous impact on household incomes depends on the size of the annual increase in Oil Palm TFP, I ran simulations based on annual increases of 2% and 1% in the Oil Palm TFP for an inelastic labor supply.

Table 4.4: Percentage Reduction in Household Income Growth (% Difference Between DF and observed economies)

TFP Shock: Oil Palm	Household Type			
	Poor, Fishing	Nonpoor, Fishing	Poor, Nonfishing	Nonpoor, Nonfishing
1%	0.2	0.7	25.1	21.2
2%	1.5	1.5	14.4	11.7
3%	1.8	1.6	10.2	8.0

Notes: Difference is calculated as shift from DF to observed economy.

For smaller increases in Oil Palm TFP, the heterogeneous effect of the disease on household incomes is magnified when the labor supply is inelastic. However, for larger increases in Oil Palm TFP, the magnitude and heterogeneous nature of the disease effect declines. This result reflects the fact that spillovers across households that result from sector-specific policy shocks may be limited by the size of the shock. Furthermore, these results suggest that policies and programs that target aggressive economic development, including those with a long-term focus on pulling households out of poverty traps (Barrett, Carter, and Chavas, 2019), may also produce short-term benefits for households in areas where Schisto is prevalent.

4.4 Discussion

While Schisto has an impact on economic growth, the structure of the labor market matters. A highly elastic labor supply allows producers to keep pace with growing demand and offset productivity losses stemming from the disease by increasing employment. When economic growth is sector-specific, the effect that the disease has is felt disproportionately by the households most active in that sector. Relaxing the assumption that wages are paid to effective labor, rather than labor time, may alter the results shown above and is a part of planned future work.

The results presented in this chapter offer a more nuanced perspective on the relationship between the disease burden of Schisto and economic growth. In contrast to previous studies that rely on aggregate measures of economic activity, the EBL model allows me to examine the mechanisms underlying this critical relationship, shining light on how the structure of labor markets and labor responsiveness contribute to the impact that Schisto can have on economic growth.

Bibliography

Anderson, Jock R. and Gershon Feder (2007). “Chapter 44 Agricultural Extension”. In: *Handbook of Agricultural Economics*. Elsevier, pp. 2343–2378. DOI: 10.1016/s1574-0072(06)03044-1. URL: https://doi.org/10.1016/s1574-0072(06)03044-1.

Barrett, Christopher B., Michael R. Carter, and Jean-Paul Chavas (2019). *The Economics of Poverty Traps*. University of Chicago Press. DOI: 10.7208/chicago/9780226574448.001.0001. URL: https://www.nber.org/books-and-chapters/economics-poverty-traps.

Bloom, David E., David Canning, Richard K. Mansfield, and Michael Moore (2007). “Demographic Change, Social Security Systems, and Savings”. In: *Journal of Monetary Economics* 54.1. Carnegie-Rochester Conference Series on Public Policy: Economic Consequences of Demographic Change in a Global Economy April 21-22, 2006, pp. 92–114. ISSN: 0304-3932. DOI: https://doi.org/10.1016/j.jmoneco.2006.12.004. URL: https://www.sciencedirect.com/science/article/pii/S0304393206002522.

Cervellati, Matteo and Uwe Sunde (2013). “Life Expectancy, Schooling, and Lifetime Labor Supply: Theory and Evidence Revisited”. In: *Econometrica* 81.5, pp. 2055–2086. ISSN: 00129682, 14680262. URL: http://www.jstor.org/stable/23524312 (visited on 07/28/2023).

Guloba, Madina M., Medard Kakuru, Sarah N. Ssewanyana, and Jakob Rauschendorfer (2021). *Employment Creation Potential, Labor Skills Requirements and Skill Gaps for Young People: A Uganda Case Study*. Brookings Institute. URL: https://www.brookings.edu/wp-content/uploads/2021/07/21.08.02-Uganda-IWOSS.pdf.

Hasnah, Euan Fleming, and Tim Coelli (Jan. 2004). “Assessing the Performance of a Nucleus Estate and Smallholder Scheme for Oil Palm Production in West Sumatra: A Stochastic Frontier Analysis”. In: *Agricultural Systems* 79.1, pp. 17–30. DOI: 10.1016/s0308-521x(03)00043-x. URL: https://doi.org/10.1016/s0308-521x(03)00043-x.

Lee, Ronald and Andrew Mason (Sept. 2006). “What Is the Demographic Dividend?” In: *Finance and Development* 43.3. URL: https://www.imf.org/external/pubs/ft/fandd/2006/09/basics.htm.

Lewis, W. Arthur (1954). “Economic Development with Unlimited Supplies of Labour”. In: *The Manchester School* 22.2, pp. 139–191. DOI: https://doi.org/10.1111/j.1467-9957.1954.tb00021.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-9957.1954.tb00021.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-9957.1954.tb00021.x.

Lindsay, Amanda R., James N. Sanchirico, Ted E. Gilliland, Rohani Ambo-Rappe, J. Edward

Taylor, Nils C. Krueck, and Peter J. Mumby (2020). "Evaluating Sustainable Development Policies in Rural Coastal Economies". In: *Proceedings of the National Academy of Sciences* 117.52, pp. 33170–33176. ISSN: 0027-8424. DOI: 10.1073/pnas.2017835117. URL: https://www.pnas.org/content/117/52/33170.

Mason, Andrew, Ronald Lee, and Jennifer Xue Jiang (Apr. 2016). "Demographic Dividends, Human Capital, and Saving". In: *The Journal of the Economics of Ageing* 7, pp. 106–122. DOI: 10.1016/j.jeoa.2016.02.004. URL: https://doi.org/10.1016/j.jeoa.2016.02.004.

Matovu, John-Mary, Francis Wasswa, Edward Bbale, and John-Bosco Oryema (2018). *Savings and Wealth Creation in Uganda: Evidence from National Transfer Accounts*. Tech. rep. Research for Transformation and Development. URL: https://www.rtdug.org/images/published_and_working_papers/SavingsWealthCreation.pdf.

Novignon, Jacob, Justice Nonvignon, and Eric Arthur (Mar. 2015). "Health Status and Labour Force Participation in Sub-Saharan Africa: A Dynamic Panel Data Analysis". In: *African Development Review* 27, pp. 14–26.

Strauss, John and Duncan Thomas (1998). "Health, Nutrition, and Economic Development". In: *Journal of Economic Literature* 36.2, pp. 766–817. ISSN: 00220515. URL: http://www.jstor.org/stable/2565122 (visited on 07/28/2023).

Taylor, J. Edward and Mateusz J. Filipski, eds. (2014). *Beyond Experiments in Development Economics: Local Economy-Wide Impact Evaluation*. Oxford: Oxford University Press.

4.A Baseline Output Shares by Household Type

Table 4.5: Baseline Output Shares by Household Type

Household	Crop	Livestock	Fishing	Oil Palm	Retail	Services
Poor, Fishing	6.1%	8.9%	52.9%	13.2%	3.3%	15.7%
Nonpoor, Fishing	5.9%	7.4%	44.6%	18.4%	8.8%	14.9%
Poor, Nonfishing	28.2%	22.5%	0.0%	34.1%	9.2%	6.0%
Nonpoor, Nonfishing	8.8%	10.0%	0.0%	30.0%	25.5%	25.8%

Notes: Each row contains sector shares of the value of all output produced the household. Values sum to 100% across each row.

Chapter 5

Alternative Specifications

5.1 Introduction

Several assumptions are required in order to produce the results shown in Chapters 3 and 4. In this chapter, I test the sensitivity of the EBL model results to three of these assumptions and discuss how results change across the three domains—biological, public health, and economic—of the human-natural environment.

The first assumption that I examine is that production in the fishing sector exhibits constant returns to scale (CRS) in *non-stock* inputs, labor and capital, and thus is increasing returns to scale (IRS) in all inputs. This assumption is important to consider, as characteristics of the local fishing sector and local factor market can determine the returns to scale that local fishers might face (Lindsay et al., 2020). To examine how the assumption of IRS in the fishing sector affects the results observed in Chapter 3, I simulate the FMP shock with CRS imposed on all inputs in the fishing sector, including the fish stock.

The second assumption that I consider is that a unit of labor time is 15% less productive due to Schisto infection. The relationship between Schisto and labor productivity is one of three links between the public health and economic domains of the human-natural environment.

Given the range of estimates from previous studies, it is worth considering how sensitive the results of the EBL model are to specification of this relationship. To examine how this modeling assumption affects the results observed in Chapter 3, I simulate the FMP, TFP, and MDA shocks with low (5%) and high (30%) values of α.

The third assumption relates to how the price of fish is determined. The results presented in Chapters 3 and 4 are based on an assumption that the price of fish is determined outside of the local economy. The extent to which local prices are determined by factors outside of the local economy can influence the impact of policy shocks (Gilliland, Sanchirico, and Taylor, 2019). In this chapter, I compare results from the FMP shock based on an alternative assumption that the price of fish is determined locally.

5.2 Returns to Scale in the Fishing Sector

To test the assumption of increasing returns to scale (IRS) in the fishing sector underlying the results presented in Chapters 3 and 4, I generate results using the FMP policy shock for an alternative scenario in which returns to scale in the fishing sector are constant (CRS). I compare 1$^{\text{st}}$-year and 10$^{\text{th}}$-year outcomes across the IRS and CRS scenarios.

Returns to scale in the fishing sector may be increasing in all inputs when technological advancements are frequent and available to individual fishers (Squires and Walden, 2021). On the other hand, returns to scale may be constant in all inputs when fishing is open access (Lokina, 2009). Specification of returns to scale in the present study is important because the marginal revenue product of any input is decreasing in total output elasticity. Using labor as an example, recall that the wage paid to effective labor E in the local economy is

$$w = \frac{p_{fish}}{\omega E_{fish}} \left[E_{fish} MPP_{E,fish} + \theta X MPP_X \right] \tag{5.1}$$

where ω is the sum of the output elasticities for all factors of production in the fishing sector.

I assume that the price of fish p_{fish} is determined outside the local economy (see Section 5.4 for an exploration of this assumption). Since fishing is open access, no opportunity cost exists for the fish stock, which results in labor and capital capturing the value that the fish stock contributes to the production process. I assume that θ, which is used to denote the share of this value that is captured by labor, is fixed over time. As a result, the wage paid to labor in the fishing sector depends on the quantities and marginal physical products (MPP) of both labor and the fish stock.

Moving from a scenario in which returns to scale are increasing implies a decline in the value of ω in Eq. (5.1). For a given wage, w, Eq. (5.1) states that a decline in the value of ω is accompanied by corresponding changes in the other terms within the bracket on the right side of the equation. Specifically, such changes could include an increase in either the amount fish harvested or the amount of labor employed in the fishing sector. To see why this is true, we recall that

$$\frac{\partial MPP_i}{\partial i} < 0 \tag{5.2}$$

for the i^{th} factor of production. Consequently, a decline in ω accompanied by an increase in the quantity of either labor or fish stock *could* satisfy Eq. (5.1).

The specification of returns to scale in the fishing sector has potential ancillary consequences for the biological and public health domains. For an example, consider a shift from the IRS scenario to the CRS scenario that results in an increase in exposure time, which in turn would *ceteris paribus* result in an increase in household infection rates and R_0. Similarly, the increase in fishing effort would result in an increase in pressure on the fish stock (Lindsay et al., 2020).

Comparing across the two specifications for returns to scale, results for all outcomes are qualitatively similar; we only observe differences in magnitude, with one exception (see Figure 5.4). Compared to the results under IRS, the magnitudes of the effects of the FMP shock under CRS are reduced for the public health and economic domains, but are enhanced for the long-term effects in the biological domain. Within the economic domain, less labor is shifted away from the fishing sector in the first year in response to the fishing capital restriction following the policy shock, which reflects the fact that factor inputs are less mobile when returns to scale are smaller. More effort remaining in the sector when returns to scale are constant is reflected in the smaller immediate declines in exposure time and harvest.

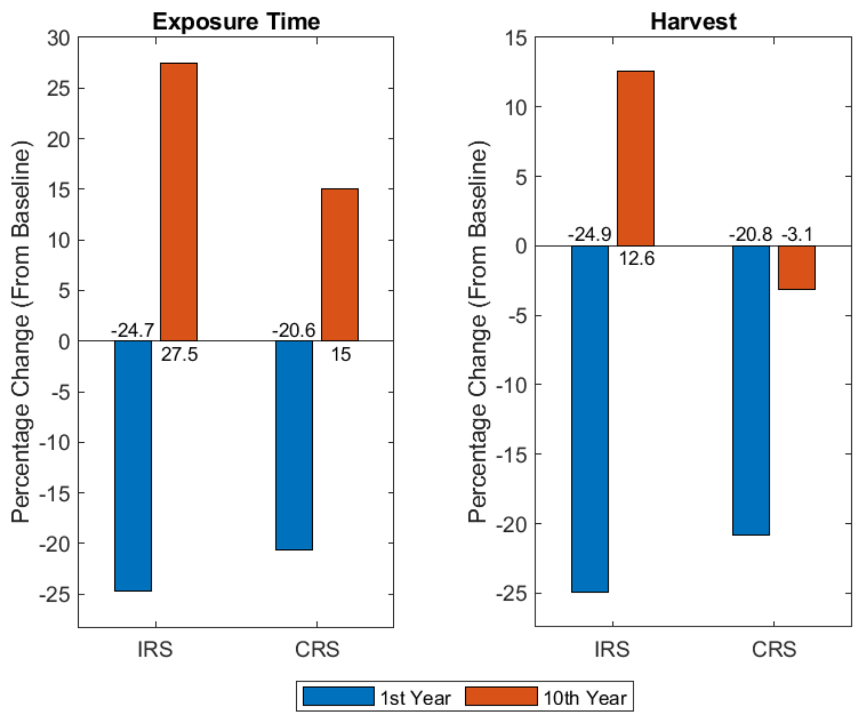


Figure 5.1: Percentage changes (relative to baseline) in exposure time and harvest resulting from the FMP shock for the IRS and CRS scenarios. Data provided in table form in Appendix 5.A. *Vertical axes differ across figures.*

Over the 10-year period effort returns to the sector, albeit to a lesser extent when returns to scale are constant. The difference, an exception to the observation that we only observe differences in magnitude, is enough that harvest does not return to baseline levels by the end of the study period under CRS.

The smaller immediate decline in effort means that household incomes decline less than in the IRS scenario. The policy shock indirectly affects nonfishing households as observed by the decline in their incomes, which is due to fishing households having less income and thus reduced expenditures in the local economy.

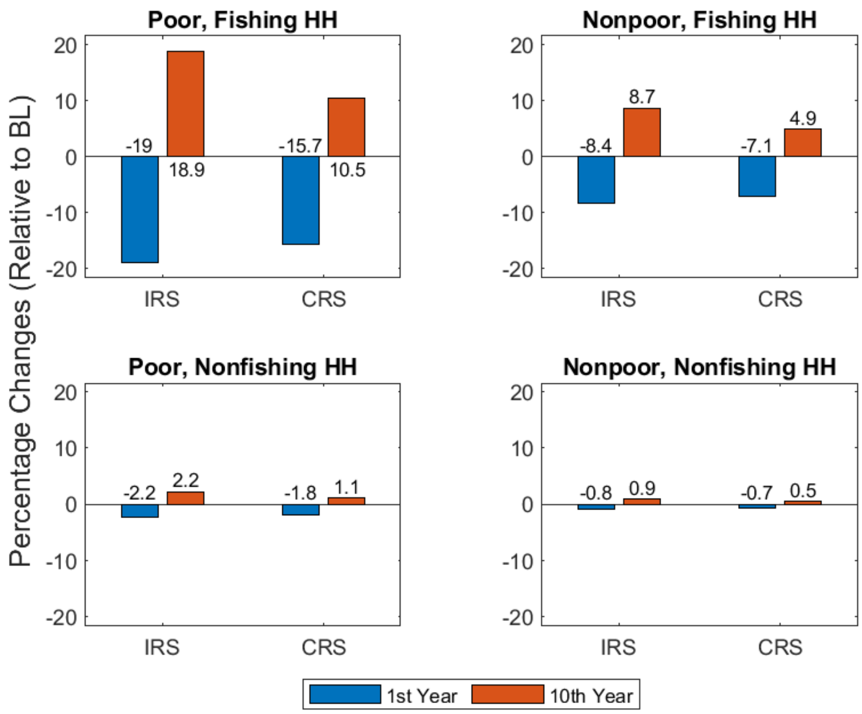


Figure 5.2: Percentage changes (relative to baseline) in household incomes resulting from the FMP shock for the IRS and CRS scenarios. Data provided in table form in Appendix 5.A.

Although household incomes do not decline as much in the first year, the smaller immediate declines in household infection rates that result from the smaller decline in exposure time is evidence of a trade-off between the economic and public health domains. The smaller reduction in effort leads to a smaller decline of approximately 25% in fish harvest, compared to results under IRS.

Within the biological domain, the fish stock recovers approximately 20% less under CRS in the first year following the policy shock, which is a consequence of the fact that more effort remains in the sector immediately after the policy shock when returns to scale are constant (Figure 5.1). Because more labor remains in the sector under CRS, neither R_0 nor aggregate

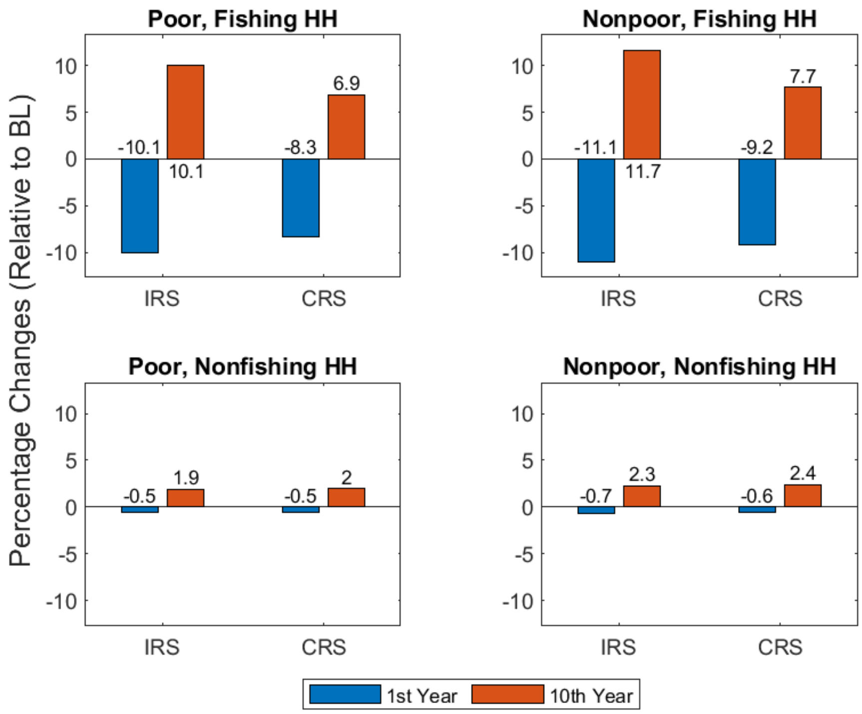


Figure 5.3: Percentage changes (relative to baseline) in household infection rates resulting from the FMP shock for the IRS and CRS scenarios. Data provided in table form in Appendix 5.A.

output decline as much in the first year following the policy shock.

As a result of fishing effort returning more slowly under CRS, the fish stock is able to recover significantly more over the study period. R_0 is lower under CRS because exposure time is reduced, although it is supported by the relative decline in aggregate output that is an outcome of the relative decline in fishing effort. In summary, these results support the conclusion that specification of the returns to scale in the fishing sector has implications for only the magnitude—not direction—of change for results across the three domains of the human-natural environment.

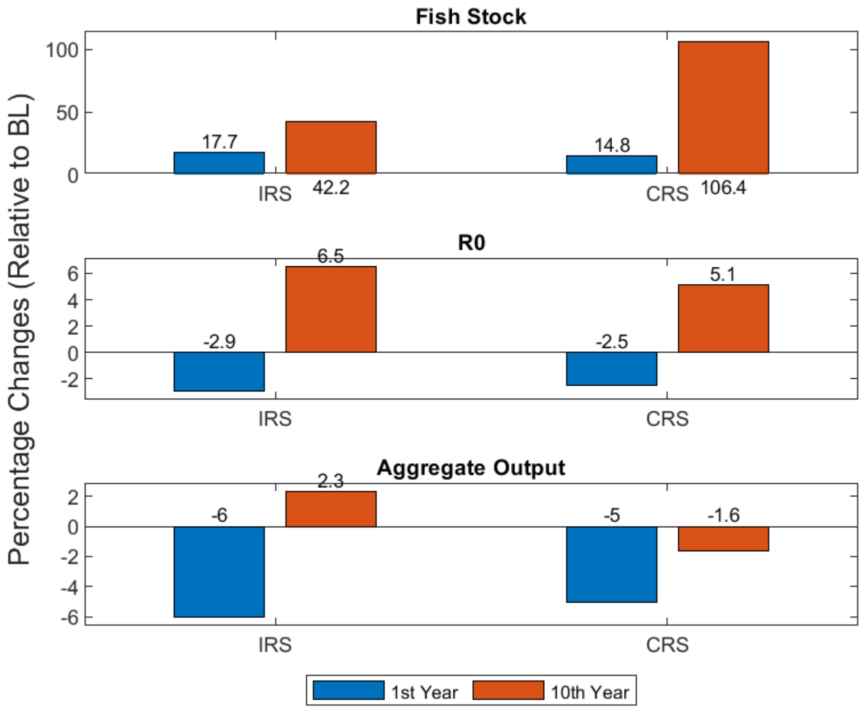


Figure 5.4: Percentage changes (relative to baseline) in Fish stock, R_0, and aggregate output resulting from the FMP shock for the IRS and CRS scenarios. Data provided in table form in Appendix 5.A. *Vertical axes differ across figures.*

5.3 Schisto and Labor Effectiveness

The results presented in Chapters 3 and 4 are based on the assumption that the parameter α, which represents the amount by which Schisto reduces the effectiveness of a unit of labor time, is equal to 15%. As discussed in Chapter 1, estimates for this value range between 5% (Fenwick and Figenschou, 1972) and 30% (Barbosa and Costa, 1981). To examine whether results are sensitive to changes in the value of α, I re-estimate the effects of the FMP, TFP, and MDA policy shocks for the minimum ($\alpha = 0.05$) and maximum ($\alpha = 0.3$) values. The importance of the parameter α in the EBL model can be seen by reflecting on the equation

$$L_{h,t} = \frac{E_{h,t}}{(1 - \alpha I_{h,t})} \tag{5.3}$$

which represents the relationship between the household supply of effective labor and its supply of labor time in year t. For a given household infection rate, I_h, the parameter α determines the difference between the two measures of labor supply. Furthermore, the measure of fishing labor time supplied by the household also appears in the equation for exposure time in year t for household h

$$\tau_{h,t} = \bar{\tau}_h + \frac{L_{h,fish,t}}{L_{h,fish,baseline}} \tag{5.4}$$

where $\bar{\tau}_h$ is constant over time and accounts for background household activities that are correlated with exposure to Schisto, such as time spent collecting water. The time-varying component of Eq. (5.4) includes the amount of fishing labor time supplied by the household, $L_{fish,h,t}$. Together, Eqs. (5.3) and (5.4) imply that when we re-estimate the effects of the three policy shocks using low (5%) and high (30%) values of α, we should expect to see differences in changes in exposure time across the two values of α.

Recalling the equation for R_0 and the state equation for the household infection rate, I_h,

$$R_0 = \frac{\beta^2 \sum_{h=1}^{H} g_h \tau_h^2 \epsilon_h^2}{\mu\gamma} \tag{5.5}$$

$$\dot{I}_h = \beta\tau_h\epsilon_h Y(1 - I_h) - \gamma I_h \tag{5.6}$$

we observe that R_0 is increasing in exposure time, since the measure of exposure time, τ_h, appears in the numerator of equation (5.5). Similarly, we also observe that $\dot{I}_h$ is increasing in τ_h. It follows that R_0 and $\dot{I}_h$ are increasing in α, even though α does not appear explicitly in the equation for R_0. Consequently, we also anticipate seeing differences in changes in R_0 and household infection rates across low and high values of α.

For all three policy shocks, changes in exposure time vary across low and high values of α. We also observe that changes in R_0 vary, as anticipated due to the implicit relationship

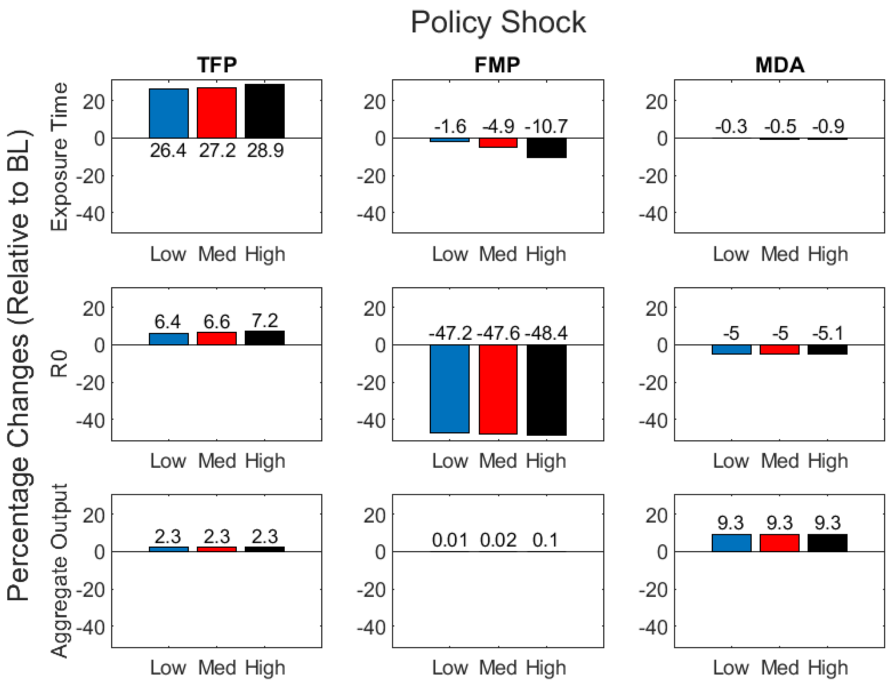


Figure 5.5: Year-10 percentage changes (relative to baseline) in exposure time, R_0, and aggregate output across policy shocks for low (5%), med (15%), and high (30%) values of α. Data provided in table form in Appendix 5.B.

between R_0 and α. However, these differences do not carry over for aggregate output, as the changes in aggregate output across policy shocks are robust to values of α.

Variation in changes in exposure time translate into differences for household infection rates, although not enough to affect the conclusions reached in Chapters 3 and 4 that are based on a value of $\alpha = 0.15$.

Differences in changes in exposure time spill partially into the economic domain. Changes in household incomes vary slightly, which is a consequence of the relationship between α, labor time, and effective labor (see Eq. (5.3)). Specifically, a larger value of α results in a smaller amount of effective labor, for a given amount of labor time.

Nevertheless, the differences in household incomes do not affect the conclusions reached in Chapters 3 and 4 that are based on a value of $\alpha = 0.15$. Furthermore, as observed in Figure

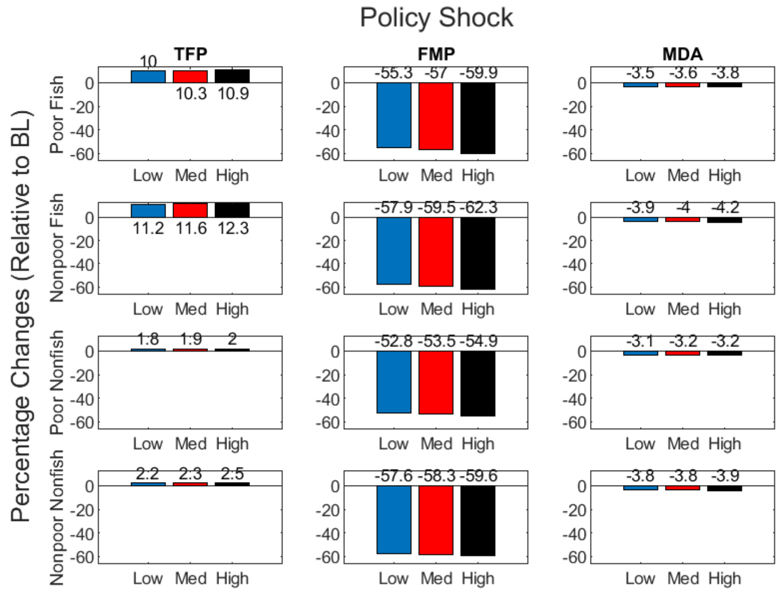


Figure 5.6: Year-10 percentage changes (relative to baseline) in household infection rates across policy shocks for low (5%), med (15%), and high (30%) values of α. Data provided in table form in Appendix 5.B.

5.5, results for aggregate output do not vary across values of α. Outcomes in the biological domain are robust to changes in the value of α (see Appendix 5.B).

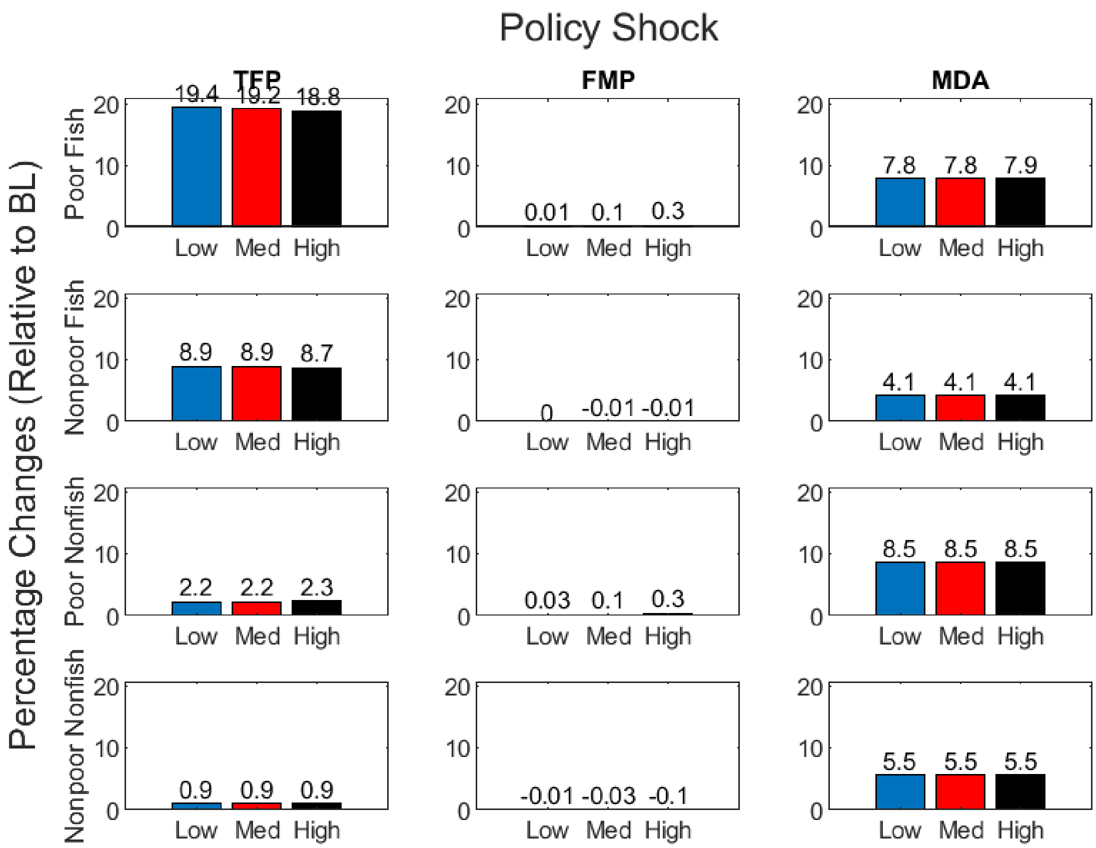


Figure 5.7: Year-10 percentage changes (relative to baseline) in household incomes across policy shocks for low (5%), med (15%), and high (30%) values of α. Data provided in table form in Appendix 5.B.

5.4 Fish Prices Determined Locally v. Exogenously

The price of fish plays an important role in fishers' decisions to allocate effort to the harvest process. Consequently, whether the price of fish is determined locally ("local" scenario) or exogenously ("exogenous" scenario) may be relevant across the three domains of the human-natural environment. The price of fish may be determined locally if transaction costs associated with import into and export from the local economy are sufficiently high. Examples of transaction costs can include the labor and equipment required to transport harvested fish so that it reaches the end consumer without spoilage. Consequently, decisions related to employing inputs, such as labor, may vary across the two trade scenarios, which could have ancillary consequences for outcomes in the biological and public health domains.

In a hypothetical scenario, an increase in the price of fish would lead to an increase in the value of the average product of labor, all else equal, which would induce an increase in demand for fishing labor. In this hypothetical scenario, the increase in the price of fish results in an increase in exposure time to Schisto. Such a price increase could be the result of a contraction in local supply or an increase in local demand. Consequently, when the price of fish is endogenous to the local economy, we anticipate that a policy shock that affects the price of fish, such as the FMP shock, may have ancillary consequences for the public health domain that are distinct from the results observed when the price of fish is determined exogenously.

Across the three policy scenarios, we only observe meaningful differences in outcomes between the two trade scenarios in the case of the FMP policy shock, which reduces fishing capital by 25% (e.g., creation of a limited entry program).

The FMP policy shock results in an initial decline in harvest in the fishing sector for both trade scenarios. When determined locally, the price of fish increases in response to the reduction in harvest by local fishers that results from the FMP policy shock (center column in Figure 5.8). In turn, local fishers react to the price increase by employing more effort in order to increase production *relative to* the *exogenous* scenario.

Since the FMP policy shock imposes a reduction in fishing capital that is fixed over the study period, the only way for local fishers to increase effort over time is to employ more labor. Thus by the 10^{th} year we observe a increase (relative to baseline) in exposure time in both trade scenarios and a corresponding increase in harvest. However, in the local trade scenario, the fish stock is approximately 15% above its level in the exogenous scenario by the end of the study period, while exposure time is approximately 20% below its level in the exogenous scenario by year 10.

The fact that a similarly sized harvest is obtainable with a larger fish stock and smaller

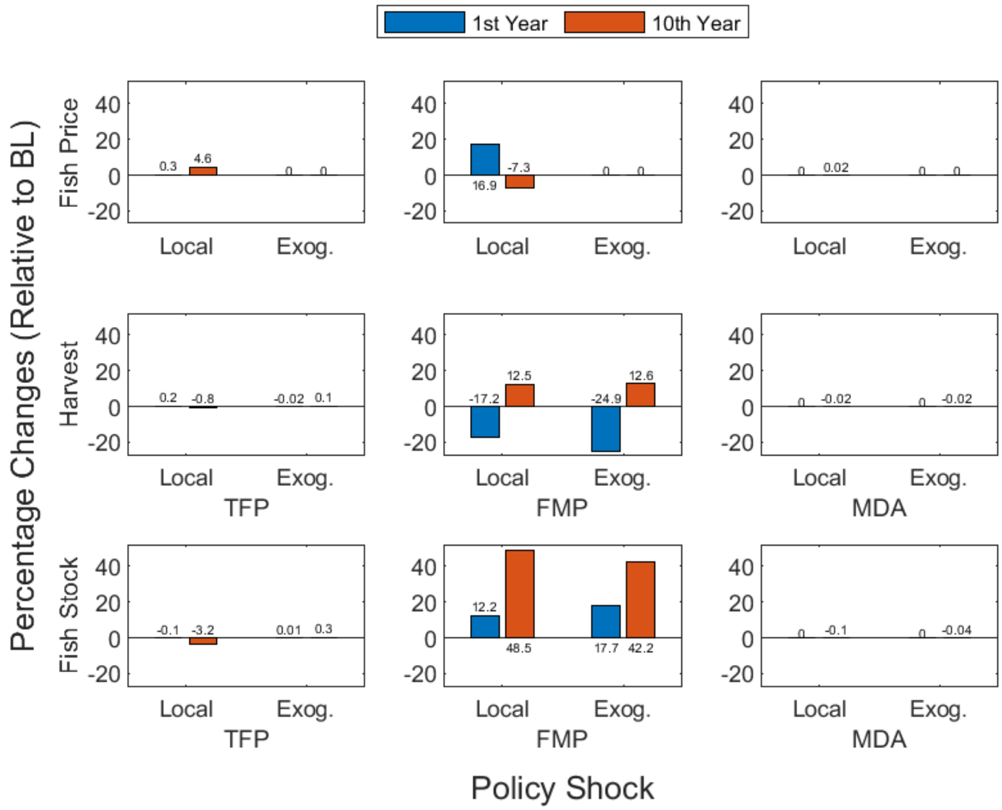


Figure 5.8: Percentage changes (relative to baseline) in fish prices, harvest, and the fish stock across the three policy shocks for the *local* and *exogenous* trade scenarios. Data provided in table form in Appendix 5.C-5.E.

amount of effort is consistent with the history of overfishing in Lake Victoria, which results in the local fishery operating where the annual fish biomass is less than the maximum sustainable yield. To see this, we recall that the net long-term revenue (NR) for the fishery is

$$NR = TSR - TC \tag{5.7}$$

where TSR is total sustainable revenue and TC is total cost (Gordon, 1954). In an open access fishery, net revenues are driven to zero, resulting in the fishery operating at point B where $TSR = TC$ in Figure 5.9.

In contrast, a fishery where effort is well-regulated could be operating at point A in Figure

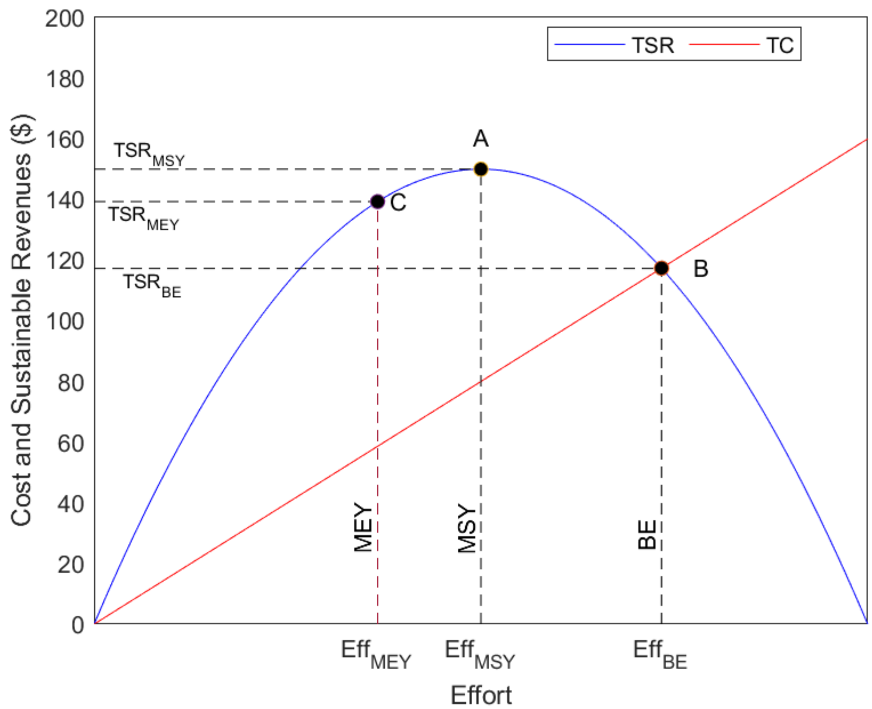


Figure 5.9: Relationship between fishing effort and the value of sustainable levels of harvest as represented in the Gordon-Schaefer Model.

5.9, where total annual harvest (yield) is the most that can obtained without drawing down future harvests, or point C, which is the point at which maximum economic rents are obtained (i.e., where the difference between TSR and TC is greatest). The results shown in Table 5.1 and above suggest that as a result of the FMP shock, the fishery operates somewhere between point A and B. The increase in fishing labor over the study period does not offset the decline in capital that results from the FMP shock, resulting in a net decline in fishing effort, which in turn results in larger harvests due to the increase in the fish stock. However, the 10 years of analysis in this study may not be enough for a new bio-economic equilibrium to be reached.

Within the public health domain, the consequence of the fishers' response to the FMP shock differs across the two scenarios. We observe a relative increase in exposure time and household infection rates in the "local" scenario. The relative increase in exposure time is enough to shift the sign of change in the value of R_0 to positive, resulting in an absolute

Table 5.1: Percentage Changes (Relative to Baseline) in Harvest, Decomposed Across Inputs.

Outcome	Local		Exogenous	
	1st Year	10th Year	1st Year	10th Year
Harvest	-17.2	12.5	-24.9	12.6
Fish Stock	12.2	48.1	17.7	42.5
Labor	0.6	2.1	-5.0	4.5
Capital	-25.0	-25.0	-25.0	-25.0

increase for this measure in the first year.

Figure 5.10: Percentage Changes (Relative to Baseline) in R_0, aggregate output, and exposure time across policy shocks for the *local* and *exogenous* trade scenarios. Data provided in table form in Appendix 5.C-5.E.

By the end of the study period, outcomes in the public health domain are relatively more favorable for the "local" scenario. Compared to the "exogenous" scenario, exposure time has increased by a smaller amount, which is consistent with the smaller increases in infection rates (see Appendix 5.C) and R_0. Similarly for the biological domain, the fish stock grows by approximately 15% more in the "local" scenario by the end of the study period. The results for the economic domain are more mixed. By the end of the study period, aggregate output is lower in the "local" scenario as a result of the relatively smaller fish harvest, compared to outcomes in the "exogenous" scenario.

5.5 Discussion

An additional assumption worthy of consideration in this chapter is the definition of poverty used to classify households in the local economy. Using the original survey data, I classify households according to whether they are fishing households and whether they are poor, which is defined as expenditures at or below a specified poverty line. The poverty line that I use is $1.04, which is a daily per capita value that I convert from Ugandan shillings using the exchange rate of 3,650 Ugandan Shillings. This poverty line is comparable to the national poverty line used by the government of Uganda and falls considerably below the World Bank poverty line of $1.90 per person (Owori, 2020).

Results presented in this dissertation are sensitive to choice of the money-based measure of poverty depicted in Figure 5.11 (Arndt and Tarp, 2017). Using the World Bank poverty line would not only result in a higher poverty rate for the local economy; it would also likely mean changes in at least some of the estimates for each type of household, including consumption shares and exposure-contamination (E-C) risk parameters.

Although expenditure-based measures may correlate positively with asset-based measures of household wealth, the lack of perfect overlap means that some income-poor are excluded in the definition of a poor household when an asset-based measure is used, and vice versa. The consequence of this exclusion is an example of the potential for bias associated with choice of poverty measure. Furthermore, money-based measures of poverty mask the multidimensional nature of poverty (Alkire and Foster, 2011). Mismeasurement and bias due to the choice

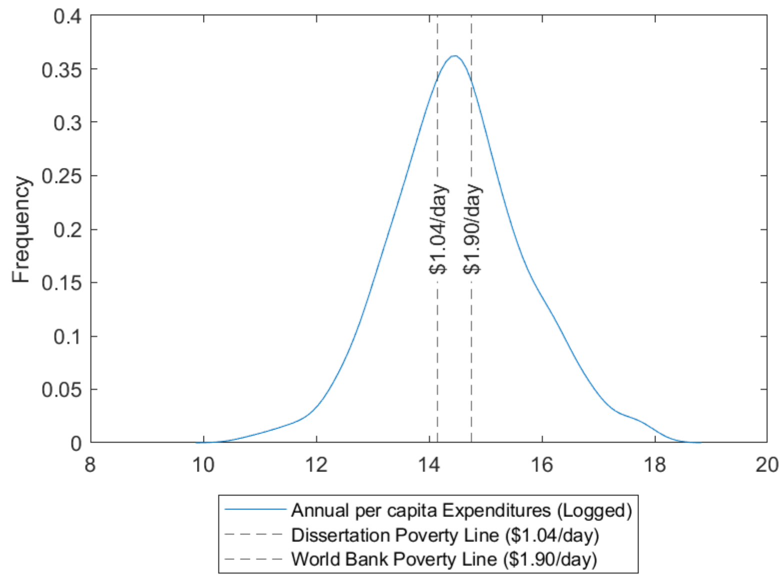


Figure 5.11: Kernel plot of annual per capita expenditures with poverty lines overlaid. Source: Original survey data.

of poverty measure can lead to biased conclusions in studies like the present one as well as mistargeting by programs and policies designed to alleviate poverty. In future work I plan to investigate this potential for bias in the current framework. Having said that, the results presented in this study are still informative on the trade-offs across the three domains but are conditional on the definition of poverty.

In this chapter, I consider alternative specifications for three key assumptions used to produce the results presented in Chapters 3 and 4. In summary, returns to scale affect the magnitude but not direction for outcomes across the three domains of the human-natural environment, which occurs because wages paid to labor respond to changes in total output elasticity. Changes in the value of α matter for measures within the public health domain and, within the economic domain, only for household incomes. Results for aggregate output and the fish stock are robust to low and high values of α.

Bibliography

Alkire, Sabina and James Foster (2011). "Counting and Multidimensional Poverty Measurement". In: *Journal of Public Economics* 95.7–8, pp. 476–487. ISSN: 0047-2727. DOI: 10.1016/j.jpubeco.2010.11.006. URL: http://dx.doi.org/10.1016/j.jpubeco.2010.11.006.

Arndt, Channing and Finn Tarp (2017). *Measuring Poverty and Wellbeing in Developing Countries*. Oxford University Press.

Barbosa, F. S. and D. P. Periera da Costa (1981). "Incapacitating Effects of Schistosomiasis Mansoni on the Productivity of Sugar-cane Cutters in Northeastern Brazil". In: *American Journal of Epidemiology* 114.1, pp. 102–111. ISSN: 0002-9262. DOI: 10.1093/oxfordjournals.aje.a113156. eprint: http://oup.prod.sis.lan/aje/article-pdf/114/1/102/226727/114-1-102.pdf. URL: https://doi.org/10.1093/oxfordjournals.aje.a113156.

Fenwick, A. and B. H. Figenschou (1972). "The Effect of Schistosoma mansoni Infection of the Productivity of Cane Cutters on a Sugar Estate in Tanzania". In: *Bull World Health Organ* 47.5, pp. 567–572. ISSN: 0042-9686. URL: https://www.ncbi.nlm.nih.gov/pubmed/4540675.

Gilliland, Ted E., James N. Sanchirico, and J. Edward Taylor (2019). "An Integrated Bioeconomic Local Economy-wide Assessment of the Environmental Impacts of Poverty Programs". In: *Proceedings of the National Academy of Sciences* 116.14, pp. 6737–6742. DOI: 10.1073/pnas.1816093116. eprint: https://www.pnas.org/content/116/14/6737.full.pdf. URL: https://www.pnas.org/content/116/14/6737.

Gordon, H. Scott (1954). "The Economic Theory of a Common-Property Resource: The Fishery". In: *Journal of Political Economy* 62.2, pp. 124–142. ISSN: 00223808, 1537534X. URL: http://www.jstor.org/stable/1825571 (visited on 03/17/2024).

Lindsay, Amanda R., James N. Sanchirico, Ted E. Gilliland, Rohani Ambo-Rappe, J. Edward Taylor, Nils C. Krueck, and Peter J. Mumby (2020). "Evaluating Sustainable Development Policies in Rural Coastal Economies". In: *Proceedings of the National Academy of Sciences* 117.52, pp. 33170–33176. ISSN: 0027-8424. DOI: 10.1073/pnas.2017835117. URL: https://www.pnas.org/content/117/52/33170.

Lokina, Razack B. (2009). "Technical efficiency and the role of skipper skill in artisanal Lake Victoria fisheries". In: *Environment and Development Economics* 14.4, pp. 497–519. DOI: 10.1017/S1355770X08004968.

Owori, Moses (2020). *Poverty in Uganda: National and Regional Data and Trends*. Fact sheet. Development Initiatives. URL: https://devinit-prod-static.ams3.cdn.digit aloceanspaces.com/media/documents/Poverty_in_Uganda_-_National_and_regional_data_and_trends.pdf.

Squires, Dale and John Walden (2021). "The Economics of Production in Marine Fisheries". In: *Handbook of Production Economics*. Springer Singapore, pp. 1–40. ISBN: 9789811034503. DOI: 10.1007/978-981-10-3450-3_34-1. URL: http://dx.doi.org/10.1007/978-981-10-3450-3_34-1.

5.A FMP Policy Shock Outcomes: Increasing and Constant Returns to Scale in the Fishing Sector

FMP Policy Shock: Percentage Changes (Relative to Baseline) in Outcomes

Outcome		Increasing Returns		Constant Returns	
		1st Year	10th Year	1st Year	10th Year
R0		-2.9	6.5	-2.5	5.1
Fish Stock		17.7	42.2	14.8	106.4
Aggregate Output		-6.0	2.3	-5.0	-1.6
Fish Harvest		-24.9	12.6	-20.8	-3.1
Exposure Time		-24.7	27.5	-20.6	15.0
Household Income	Poor, Fishing	-19.0	18.9	-15.7	10.5
	Nonpoor, Fishing	-8.4	8.7	-7.1	4.9
	Poor, Nonfishing	-2.2	2.2	-1.8	1.1
	Nonpoor, Nonfishing	-0.8	0.9	-0.7	0.5
Infection Rates	Poor, Fishing	-10.1	10.1	-8.3	6.9
	Nonpoor, Fishing	-11.1	11.7	-9.2	7.7
	Poor, Nonfishing	-0.5	1.9	-0.5	2.0
	Nonpoor, Nonfishing	-0.7	2.3	-0.6	2.4

5.B High and Low Values of α

Percentage Changes (Relative to Baseline) in Outcomes

Outcome		FMP		MDA		TFP	
		Low	High	Low	High	Low	High
R_0		6.4	7.2	-47.2	-48.4	-5.0	-5.1
Fish Stock		42.6	42.6	0.0	-0.1	0.3	0.3
Aggregate Output		2.3	2.3	0.0	0.1	9.3	9.3
Fish Harvest		12.6	12.6	0.0	0.0	0.1	0.1
Exposure Time (τ_h)		26.4	28.9	-1.6	-10.7	-0.3	-0.9
Household Income	Poor, Fishing	19.4	18.8	0.0	0.3	7.8	7.9
	Nonpoor, Fishing	8.9	8.7	0.0	0.0	4.0	4.1
	Poor, Nonfishing	2.2	2.3	0.0	0.3	8.5	8.5
	Nonpoor, Nonfishing	0.9	0.9	0.0	-0.1	5.5	5.5
Infection Rates	Poor, Fishing	10.0	10.9	-55.3	-59.9	-3.5	-3.8
	Nonpoor, Fishing	11.2	12.3	-57.9	-62.2	-3.9	-4.2
	Poor, Nonfishing	1.8	2.0	-52.8	-54.9	-3.1	-3.2
	Nonpoor, Nonfishing	2.2	2.5	-57.5	-59.6	-3.8	-3.9

Notes: Low value of $\alpha = 0.05$, high value of $\alpha = 0.3$.

5.C FMP Policy Shock Outcomes: Fish Prices Determined Locally, Exogenously

FMP Policy Shock: Percentage Changes (Relative to Baseline) in Outcomes

Outcome		Local		Exogenous	
		1st Year	10th Year	1st Year	10th Year
R_0		0.8	4.5	-2.9	6.5
Fish Stock		12.2	48.5	17.7	42.2
Aggregate Output		-1.5	0.7	-6.0	2.3
Exposure Time		-17.2	12.5	-24.9	12.6
Fish Harvest		-0.1	17.5	-24.7	23.8
Fish Price		16.9	-7.3	0.0	0.0
Household Income	Poor, Fishing	-0.8	13.1	-18.9	14.4
	Nonpoor, Fishing	-2.8	8.0	-8.5	4.8
	Poor, Nonfishing	-0.6	1.9	-2.2	2.4
	Nonpoor, Nonfishing	-0.7	1.1	-0.8	0.8
Infection Rates	Poor, Fishing	0.5	7.1	-10.1	9.8
	Nonpoor, Fishing	0.6	8.0	-11.2	9.6
	Poor, Nonfishing	0.5	1.5	-0.6	1.8
	Nonpoor, Nonfishing	0.6	1.8	-0.7	2.2

5.D TFP Policy Shock Outcomes: Fish Prices Determined Locally, Exogenously

TFP Policy Shock: Percentage Changes (Relative to Baseline) in Outcomes

Outcome		Local 1st Year	Local 10th Year	Exogenous 1st Year	Exogenous 10th Year
R_0		-0.4	-4.6	-0.5	-5.2
FishStock		-0.1	-3.2	0.0	0.3
Aggregate Output		0.9	10.0	0.9	9.6
Exposure Time		0.1	-0.8	0.0	0.1
Fish Harvest		0.4	2.7	-0.1	-0.4
Fish Price		0.3	4.6	0.0	0.0
Household Income	Poor, Fishing	1.0	9.8	0.7	5.8
	Nonpoor, Fishing	0.5	4.0	0.4	3.4
	Poor, Nonfishing	0.8	8.5	0.8	6.7
	Nonpoor, Nonfishing	0.5	5.3	0.5	5.8
Infection Rates	Poor, Fishing	-0.1	-2.3	-0.3	-3.6
	Nonpoor, Fishing	-0.1	-2.6	-0.4	-4.0
	Poor, Nonfishing	-0.3	-3.0	-0.3	-3.2
	Nonpoor, Nonfishing	-0.3	-3.6	-0.3	-3.8

5.E MDA Policy Shock Outcomes: Fish Prices Determined Locally, Exogenously

MDA Policy Shock: Percentage Changes (Relative to Baseline) in Outcomes

Outcome		Local		Exogenous	
		1st Year	10th Year	1st Year	10th Year
R_0		-22.8	-47.6	-22.8	-47.6
FishStock		0.0	-0.1	0.0	0.0
Aggregate Output		0.0	0.0	0.0	0.0
Exposure Time		0.0	0.0	0.0	0.0
Fish Harvest		0.0	-4.9	0.0	-4.9
Fish Price		0.0	0.0	0.0	0.0
Household Income	Poor, Fishing	0.0	0.1	0.0	0.1
	Nonpoor, Fishing	0.0	0.0	0.0	0.0
	Poor, Nonfishing	0.0	0.1	0.0	0.1
	Nonpoor, Nonfishing	0.0	0.0	0.0	0.0
Infection Rates	Poor, Fishing	-19.2	-57.0	-19.2	-58.7
	Nonpoor, Fishing	-20.9	-59.5	-20.9	-61.1
	Poor, Nonfishing	-17.9	-53.5	-17.9	-55.4
	Nonpoor, Nonfishing	-20.9	-58.3	-20.9	-59.9

Chapter 6

Conclusion

Widely considered to be diseases of poverty, NTDs have deleterious consequences for development due to their effect on health and economic outcomes across the socioeconomic spectrum. In this dissertation, I consider how policies that target one domain of the human-natural environment—public health, biological, or economic—can have ancillary consequences for outcomes in the two other domains, with a focus on how such policy shocks may affect the prevalence of Schisto, the 2$^{\text{nd}}$ most common NTD behind Malaria.

For my methodology, I develop a coupled model of the human-natural environment for a small economy in the Ugandan region of Lake Victoria, Africa. I focus on four links between the three component models in order to highlight the interconnectedness of the three domains. The first link characterizes the capacity for public investment in disease prevention and mitigation. I represent this link by expressing two of the Epi component parameters as functions of aggregate output in the local economy. The second link highlights how labor allocation decisions impact disease prevalence, and is represented by exposure time to the disease, as measured by fishing labor time. The third link captures the impact that Schisto has on labor productivity, and is represented by expressing effective labor as a function of household infection rates. The fourth link portrays the relationship between the stock of fish targeted by local fishers and fishing effort.

In Chapter 3, I model three types of policy shocks. The TFP policy shock represents yield-enhancing investments in the local Oil Palm sector. Oil palm is an important cash crop for local households and represents an alternative source of income in an economy that has historically been dependent on the fishing sector. The fisheries management policy (FMP) shock represents regulation of fishing effort and is designed to address the problem of persistent overfishing in Lake Victoria, which has led to lower returns to fishing effort and negative consequences for the environment. The MDA shock represents community-based drug treatment of the disease, which is a common approach to combating Schisto.

Yield-improving policies such as the TFP shock can produce the ancillary benefit of reducing household infection rates by raising incomes and, consequently, aggregate output, which increases the capacity for public investment in disease prevention and mitigation. Additionally, the expansionary effect of the TFP shock draws labor away from fishing, which results in less exposure time. However, the decline in disease prevalence is due largely to the increase in household incomes and aggregate output. Consequently, the TFP shock on its own may not be an adequate tool for reducing labor-associated exposure time to the disease.

By regulating fishing effort, fisheries management policies of the sort modeled in Chapter 3 produce long-term benefits for the fishery by increasing the biomass of the fish stock, which results in greater returns to future fishing effort. However, understanding the ancillary consequences associated with such policies can shed light on how policy may inadvertently perpetuate disease-based poverty traps. In the short term, incomes for fishing households (and, indirectly, for nonfishing households) fall due to the restrictions on fishing effort. The resulting decline in aggregate output leads to an increase in disease prevalence. Over time, effort returns to the sector in the form of fishing labor. However, the resulting increase in household incomes and aggregate output is accompanied by an increase in exposure time to the disease. We therefore conclude that in isolation, efforts to regulate fishing effort may inadvertently contribute to disease prevalence.

On its own, the MDA shock has the effect of reducing prevalence of Schisto. However, absent a complementary policy such as the TFP shock, no incentives exist to shift household labor away from hazardous conditions found in the fishing sector that lead to exposure to the disease. When the two policies are enacted concurrently, we observe a significant reduction in disease prevalence, which occurs because of the drug treatment and because of the increase in aggregate output, as well as a small decline in exposure time to the disease.

In Chapter 4, I construct a disease-free (DF) counterfactual of the local economy by eliminating the impact that the disease has on labor productivity in the first year after implementation of the TFP policy shock. I compare outcomes between the DF scenario and the observed local economy across two types of labor market structures: one in which the labor supply is highly elastic and one in which the labor supply is unit elastic. From the results of this analysis, we observe that when labor market frictions are present that lead to low supply elasticity, the ability for households to take advantage of growth in a cash crop sector is reduced due to the presence of Schisto.

In Chapter 5, I consider alternative specifications for three important assumptions required for the analysis conducted in Chapters 3 and 4. Varying the impact that Schisto has on the ability to work between minimum and maximum values as defined in previous literature, I find no qualitative differences in outcomes across the three domains, which suggests that the results presented in Chapters are robust to specification of this relationship. I also find that the assumption of returns to scale in the fishing sector does drive differences in magnitude for the results observed in Chapter 3, but the differences do not imply a change in conclusions based on these results.

Given the gender-segregated nature of labor commonplace in many developing countries, a valid criticism of the model used in this dissertation is that it may not adequately characterize how female members of the household allocate their labor. This criticism is valid because the measure of a household's exposure time to the disease has a time-varying component, consisting of fishing labor time, and a time-invariant component, which consists of time spent collecting water, cleaning, recreating, and other means by which exposure to the disease occurs. A key feature of many of the activities included in this latter component is domestic production, which is an important and yet often-unmeasured contributor to household welfare that is typically (and Uganda is no exception) the responsibility of female household members. A more inclusive measure of exposure time would reflect the reality that policy shocks of the type modeled in this dissertation can affect labor allocation decisions for all production activities, including those for which time spent is not explicitly assigned a market value.