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Master's Thesis

Does Exposure to Deforestation Affect Subjective Well-Being?

Evidence from Sub-Saharan Africa

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1 Abstract

Forests' role for climate change mitigation provides a strong global incentive to halt deforestation. Despite global efforts to the contrary, tropical deforestation persists often under the premise of promoting short-term, local economic development through land cover conversion. I conduct a comparative study of 32 countries in Sub-Saharan Africa to test whether deforestation does in fact change people's well-being at a local scale. Combining annual survey data for 2016-2019 with remote-sensed land cover and land use data, two metrics of exposure to deforestation are calculated based on the loss of forest cover and increase in forest attrition around respondents' locations. I find that, on average, exposure to forest cover loss has a statistically significant negative effect on respondents' subjective well-being. This effect varies widely across regions and countries in Sub-Saharan Africa and I am able to identify particularly vulnerable polities that would benefit most from abating any further forest loss.

2 Introduction

Forests' major role as carbon sinks in the fight against climate change (Smith et al., 2023) has motivated great interest in policies geared towards abating potential carbon emissions from deforestation (Balboni et al., 2022; Barbier et al., 2020; Gibbs et al., 2018). Land-based ecosystems absorbed around 30 per cent of the carbon emissions generated through human activity in the last decade (Pathak et al., 2022, p. TS.5.6.1). While restoration of forests remains among the most effective strategies for climate change mitigation (Griscom et al., 2017; Nabuurs et al., 2022), with the potential to store an equivalent of 25 percent of the current atmospheric carbon pool (Bastin et al., 2019), deforestation accounts for 45 percent of the total emissions from agriculture, forestry and other land-use worldwide (Pathak et al., 2022, p. TS.5.6.1), making halting it a priority in and of itself. What has received less attention to date, though, are those negative effects of deforestation which are not directly linked to carbon storage (Ellison et al., 2017), and which evolve predominantly in local rather than global contexts.

Forests are of fundamental importance for the socioeconomic and ecological systems that human societies operate in. Recent evidence documents forests' ability to regulate hydrological cycles (Ellison et al., 2017), provide access to safe drinking water (Mapulanga & Naito, 2019), mitigate local temperature extremes (Ellison et al., 2017), reduce infectious disease exposure (Garg, 2019), and improve mental health (Bolton et al., 2022; Wigand et al., 2022) in people near them. Forests are also popular recreational spaces and hold cultural or spiritual significance in many parts of the world.

Moreover, millions of people who live in poverty rely on the home consumption and sale of non-timber forestry products (or NTFPs), derived from living forests, to support their livelihoods (Angelsen et al., 2014; Shackleton & Pandey, 2014; Sunderlin et al., 2005). Often entire local economies based on forest resources emerge in this context, generating new employment opportunities and income streams (Agrawal et al., 2013; Razafindratsima et al., 2021; Whiteman et al., 2015). Thus, vulnerable populations in particular utilize forest ecosystems as natural insurance against, both, income and supply shocks (Angelsen et al., 2014; Pritchard et al., 2020; Rasmussen et al., 2017). All this has given rise to a growing literature that ascribes an imminent role to forests for the global development policy agenda more broadly.

Beyond climate action as envisioned in SDG 13, they serve important functions in relation to poverty eradication and the promotion of food security, good health and well-being, and access to clean water as codified in SDGs 1, 2, 3 and 6 (Jagger et al., 2022; Miller et al., 2022). Additionally, forests are fundamental building blocks of sustainable communities (SDG 11), hold vast potential for responsible consumption and production (SDG 12) and harbor most of Earth's terrestrial biodiversity (SDG 15) across all three of its components – ecosystem, species and genetic diversity (FAO, 2022; FAO & UNEP, 2020).

Where the value of conservation is not deemed exceptionally high, forests are likely not left completely undisturbed. What follows is that about two thirds of the world's forests are currently used to some extent for the extraction of timber (FAO & UNEP, 2020). Economic theory suggests that the optimal rate of extraction from a renewable resource, like timber in a forest, may vary with the land owner's cost structure. In particular, if non-timber benefits are not properly accounted for, interest rates are high, and regrowth slow, it may be lucrative to clear a forest once and for all, and subsequently convert the land to an alternative land use (Balboni et al., 2022). While many other factors, such as market access, openness to trade, agricultural productivity, and credit constraints play an intermediary role, it is generally acknowledged by environmental economists that the economically optimal rate of extraction tends to be higher than the forest's maximum carrying capacity (Conrad & Rondeau, 2020) and may as well exceed the social optimum, thus causing an externality.

Forests' importance for global climate change mitigation alone is arguably large enough to "turn the tide on deforestation" in the words of the UN Secretary General (FAO, 2021). Through initiatives like Collaborative Partnership on Forests (FAO, 2023) and the New York Declaration on Forests (Forest Declaration, 2021), the United Nations have spearheaded efforts to stop natural forest loss all together by 2030. The economic benefit from conserving the Amazon alone is estimated to be US$ 8.2 billion per year (Strand et al., 2018) and in many parts of the rainforest, that economic benefit far outweighs the short-term gain of tearing it down (Brouwer et al., 2022).

Notwithstanding the importance of local ecosystem services provided by forests, their protection against deforestation is rarely argued for in terms of protecting the local population from loosing access to these benefits. The global policy discourse tends to exclude those welfare effects of deforestation that materialize locally and in the short term. Continuing deforestation in many parts of the world coincide with large vulnerable populations, who especially depend on the largely non-monetized and publicly available benefits that forests provide. This adds another layer of urgency to halting the loss of forest ecosystems; one that is more immediate and might convey a greater sense of urgency to local leaders and policy entrepreneurs than the global climate agenda generally does. It gives rise to the following question, which this paper sets out to answer: How is people's well-being affected by nearby deforestation?

To empirically address this research question, I focus on 32 countries in Sub-Saharan Africa (SSA). This group of countries was purposefully chosen for this study because SSA exhibits several characteristics that are relevant to the research question. They are outlined in Section 3. A brief review of the literature on forests' ecosystem services and the applicable economic theory in Section 4 serves to formulate expectations for the empirical exercise that follows. The primary hypothesis is that, controlling for income effects, the impact of deforestation on people's well-being is a negative one. A novel approach to measuring experienced deforestation through spatially explicit data is proposed in Section 5.

Section 6 discusses the data used in this study and outlines how the independent variables are constructed. Combining survey responses from the Gallup World Poll (GWP) with Google's Dynamic World (DW) Land Use and Land Cover (LULC) classes dataset, allows for spatially explicit identification of respondents' immediate exposure to deforestation over a four-year period (2016-2019). Section 7 outlines the statistical inference methods used to estimate the effect of local deforestation on SWB. The results are presented in Section 9. For the whole sample, there is evidence of persistent negative effects of forest cover loss. Taking the analysis to the regional level evidences persistent negative effects of forest cover loss and forest attrition in Southern African countries and no significant effect in the remaining regions of SSA, on average. At a closer look, effect significance and size vary considerably among countries. Section 10 concludes.

3 Deforestation, Economic Development, and Forest Dependency in SSA

Global deforestation has declined since 2010 and net forest cover is once again increasing. Government initiatives and international moratoria were somewhat successful in reducing deforestation, prominently in the Amazon between 2004 and 2015, while regrowth and regeneration mostly occurred in Europe, Eurasia and North America (Pathak et al., 2022, p. 57). Leading up to this cautiously optimistic outlook is a long and varied history of large-scale land cover conversion by human societies. Figure 1 shows how forested areas and wild grasslands gave place to other land use classes since the last ice age. Almost half of these areas have been converted into agricultural land, especially dedicated to cattle grazing.

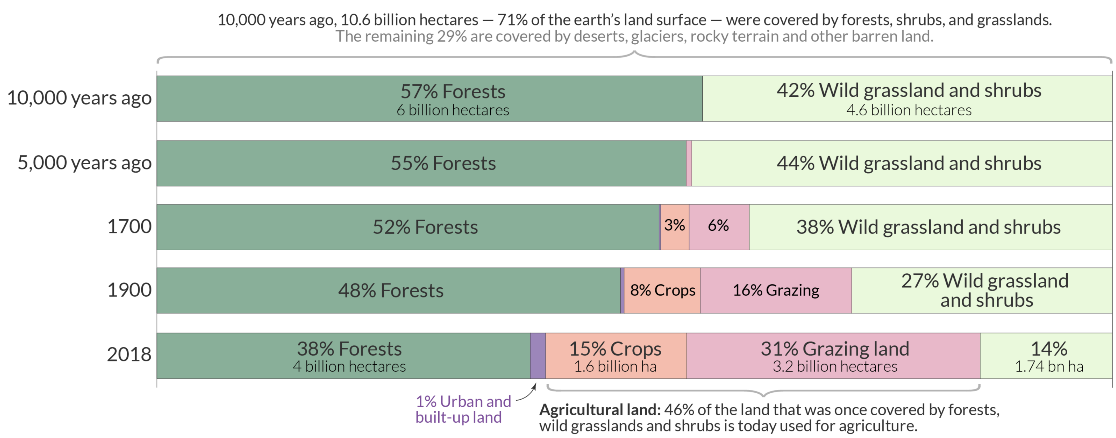

Figure 1: Forest cover conversion since the last ice age.

Between 1990 and 2020, poorer countries with problems of food insecurity have consistently had high rates of forest loss. To see this, Figure 2 plots the forest area in million hectares for the seven countries that hold the largest forests on earth, as well as for some country groups of interest. Out of these, only China has managed to significantly increase forest cover between 1990 and 2020. While forest cover has remained largely constant for countries such as Russia, the USA, or Canada, it is rapidly decreasing in Brazil, Indonesia, and the Democratic Republic of the Congo. Decline in

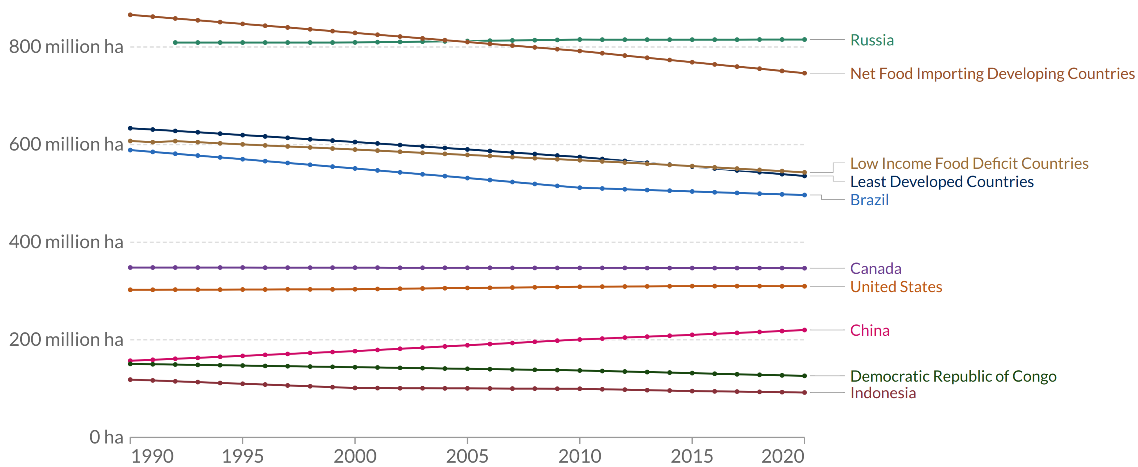

Figure 2: Forest cover by (group of) countries.

forest cover is especially pronounced in Net Food Importing Developing Countries, Low Income Food Deficit Countries and Least Developed Countries (For definitions, see Ritchie & Roser, 2021). In fact, since the 1990s, temperate forests have gained forest cover and global forest loss has been exclusively driven by tropical deforestation (Pathak et al., 2022). This coincides with the socioeconomic divide between the Global North and South, with richer nations having considerably less deforestation than poorer ones.

Research by Crespo Cuaresma & Heger (2019) confirms that SSA countries, and low-income countries more generally, have the highest deforestation-development elasticity. Still, the literature attests positive marginal effects in terms of economic performance to both forest conversion and protection, which leaves the direction of the composite effect ambiguous. Much of the optimistic viewpoint follows the broader hypothesis of an "Environmental Kuznets Curve", according to which environmental quality first declines and then resurges as a function of economic growth (Andrée et al., 2019). On the other hand, Miller & Hajjar (2020) argue that, while the benefits of conversion are often immediate and short-lived (like agricultural profits from cropping on soil in cleared rain forests), they are arguably outweighed by the long term benefits of living forest ecosystems that are lost in the process.

One way to frame the correlation between deforestation and economic development is through food security. Efforts to increase food production through domestic agriculture result in deforestation by converting forested lands to crop lands (Girard et al., 2021). In some instances, this coping mechanism is used in an effort not to increase but to maintain agricultural output in the face of declining crop productivity due to climate change(Emediegwu et al., 2022; Schlenker & Lobell, 2010). However, countries in SSA seem to be facing an intertemporal trade-off between converting forests and stabilizing output in the short term while risking to increase their exposure to drought risk, including declines in both ground water retention and rainfall (Duku & Hein, 2021), in the future (Bamwesigye et al., 2019).

Even in the short term, the net-gains from deforestation are dubious at best. The problem lies with the way in which these gains are measured. While it is true that both profits from timber and agriculture on newly cleared land contribute to economic production, there are also countless informal and non-monetized channels through which intact forests positively affect people's lives, both in economic terms and beyond. Unlike forestry and agriculture, though, these ecosystem services are largely ignored by aggregate economic metrics of output like GDP (Miller & Hajjar, 2020; Razafindratsima et al., 2021; Scoones et al., 1992; Shackleton & Pandey, 2014) which, in turn, leads to negative externalities and lack of funding for conservation relative to the social optimum (Brancalion et al., 2017; Shyamsundar et al., 2021; Waldron et al., 2013).

This is particularly problematic as millions of people living in poverty rely on forest and tree resources to support their livelihoods, both for subsistence and sale (Angelsen et al., 2014; Shackleton et al., 2007; Sunderlin et al., 2005; Sunderlin, 2006).[1] The (non-timber) forest goods and environmental services in question include food, fodder, fuel, medicine, soil fertility, water retention, carbon sequestration, tourism potential, and shelter among others (Razafindratsima et al., 2021; Shyamsundar et al., 2020). The resulting local economies based on forest resources have also been shown to generate income through employment (Agrawal et al., 2013; Razafindratsima

[1]Angelsen et al. (2014) report that forests contribute an average of 27% of household income in communities living within or in proximity to them. In some states in India, forests account for 30% of total income (Damania et al., 2020).

et al., 2021; Whiteman et al., 2015). Moreover, evidence suggests that vulnerable populations, in particular, benefit from forests as a natural insurance mechanism in coping with shocks (Pritchard et al., 2020; Rasmussen et al., 2017; Wunder et al., 2014).

These insights stem primarily from small, context specific case studies the external validity of which is unclear. Six recent papers systematically map the academic and grey literature to elucidate what can be reliably known about the processes that link tree-based systems and poverty. They find common trends, and identify areas that need further research. Agrawal et al. (2018), Cheng et al. (2019) and Miller & Hajjar (2020) leverage insights from studies inside forests, while Castle et al. (2022), Waldron et al. (2017) and Miller et al. (2020) focus on tree-based systems outside forests, specifically those managed in a range of agroforestry systems.

The majority of the evidence base concerns links between productivity strategies (e.g. forest management, agroforestry, and habitat management) and monetary income. A second strand of research examines how different modes of governance - including individual land rights and community management - affect monetary income from forest goods (Cheng et al., 2019). The impacts of investment-based interventions (i.e. enhancing produced, human, and social capitals) and the impacts of forest-based interventions on financial capital (savings, debt), non-monetary benefits, and health are less well studied and remain contested. (Cheng et al., 2019)

Jagger et al. (2022) identify four states of forest-poverty dynamics: durable improvements in well-being (shifts out of poor or extreme poor status), Maintenance of status quo (any horizontal trajectory including being trapped in poverty), transience around poor or extreme poor status (oscillation around poor or extreme poor status) and durable declines in well-being (into poor or extremely poor status). They are the first in the literature to add potentially negative externalities of forests on poverty status to a conceptual framework. Mechanisms at work might include crop raiding by wild animals, zoonotic disease risk, and the special case of geographic poverty traps, which can occur in remote forested areas.

In this context, the apparent trade-offs epitomized by the Environmental Kuznets Curve become apparent once again. Some forest-based strategies capable of improving local livelihoods may have negative externalities on ecosystem health. Commercial plantations, for instance, have a relatively high positive impact on the incomes of households - through asset ownership or employment[2] - but amount to a concern for ecosystem health (Gomes et al., 2020; Shackleton et al., 2007). The same is true, to varying degrees, for ecotourism, which has been linked to deforestation (Brandt & Buckley, 2018). Different strategies may lead to heterogeneous results in the local population. As Miller & Hajjar (2020) point out, "[a]ssessing the potential of forests to alleviate poverty over time is important in relation to both those who may have relied on forests to permanently find their way out of poverty, and those who may be at risk of becoming poor due to forest resource degradation" (Miller & Hajjar, 2020, p. 5). To achieve net poverty alleviation, it is thus necessary to design strategies carefully so that they lift some out of poverty without plunging others into it (Krishna, 2004, 2010).

Not considering these longer term dynamics, the opportunity cost of forest maintenance from the perspective of poverty alleviation has long been seen as prohibitively high; "forests are likely to be seen as inferior to other forms of rural poverty reduction that imply forest conversion to agriculture or other more extractive approaches, which may deliver results in the near term, but have less certain long-term impacts"(Miller & Hajjar, 2020, p. 5). Climate change, and ensuing fluctuations in crop production and income, may result in forest-based livelihood strategies becoming more favorable options, at least in tropical forest contexts (Wunder et al., 2018).

Indeed, climate change, the loss of biodiversity and other environmental issues push planetary boundaries (Rockström et al., 2009; Steffen et al., 2015) and threaten to undo the progress in poverty alleviation that has been made globally over the past decades (O'Neill et al., 2018). They also challenge more recent efforts to ensure that progress extends to populations that continue to be marginalized (Raworth, 2017). Therefore, "forests and tree-based systems take on particular importance, not only for expanding human well-being by reducing poverty and bringing more

[2] There is evidence, though, that plantations might contribute to poverty when property rights to land are not secured in favor of the local population (Andersson et al., 2016).

widespread prosperity, but for doing so in a way that is sustained over time" (Miller et al., 2022, p. 3).

While it is, thus, well-established that forests and trees support poor people to improve their well-being or mitigate risks, their role in helping people move permanently out of poverty remains contended (Jagger et al., 2022; Miller et al., 2021; Razafindratsima et al., 2021; Shyamsundar et al., 2020). Globally, around 40% of the extreme rural poor - or some 250 million people - live in forest and savannah areas (FAO & UNEP, 2020). Many of the variables necessary to properly disentangle the effect of forests from that of geographical and socioemmconomic isolation[3] tend to go unobserved (Sunderlin et al., 2008; see also Newton et al., 2020). Single country case studies have gone some way to uncover patterns of forest-poverty overlap (e.g., Sunderlin et al., 2008), but there has not been a comprehensive international study of this kind to date (Miller et al., 2022).

Another shortcoming that is commonly identified is the focus on monetary poverty metrics[4] because they fail to adequately capture the effects that forests induce onto poverty. The greater part of resource benefits from forests are non-market goods and services, which are typically absent from household surveys, as are adequate accounts of subsistence consumption (Jagger et al., 2022) or income generated from informal or illegal activities (which mostly remain unreported, see Angelsen et al., 2014). The use of monetary metrics used in evaluating forest-based interventions has arguably contributed to the fact that they remain largely unrecognized by policy actors (Miller & Hajjar, 2020; Razafindratsima et al., 2021; Scoones et al., 1992; Shackleton & Pandey, 2014) and lack funding in many countries (Brancalion et al., 2017; Shyamsundar et al., 2021; Waldron et al., 2013).

Jagger et al. (2022) note that temporal, spatial, and contextual dimensions of change have, to date, been understudied: "[t]he weak evidence base limits our understanding of the relationship between forests and poverty, and serves as a barrier to policymakers and other key stakehold-

[3] Populations in remote forest landscapes may find themselves in a poverty trap because of limited opportunities to participate in labor and goods markets as well as asset accumulation.

[4] Most common poverty statistics are calculated by comparing household income or expenditure data against a poverty line; for an overview and extensions see, e.g., Ravallion (2020) and Sen (1976).

ers as they weigh the relative effectiveness of forests and trees to support poverty alleviation efforts"(Jagger et al., 2022, p. 7). They conclude that "research on forest-poverty dynamics [should] be framed more broadly across longer time-frames (up to decades), across larger or nested spatial scales, and contextualized within the landscape, regional, or national settings where it is conducted". This coincides with Hajjar et al. (2021), who identify broadening the spatial and temporal extent of forest-poverty analyses as one of six emerging priorities at the research frontier.

According to them, "new data sources, including satellite imagery of land use and land cover change and spatially explicit socio-economic datasets from continuous data collection efforts, present promising opportunities to address current knowledge gaps on forest-poverty dynamics" (p. 2.). This paper continues this line of inquiry in four ways: (1) through its use of subjective well-being (SWB) rather than monetary metrics as its response variable of interest, (2) through its use of high resolution LULC data to identify deforested areas, (3) through defining deforestation exposure not based on (population-weighted) national statistics but through spatially explicit area statistics, and (4) through its comparative perspective, estimating local (sub-national and location specific) well-being effects across 32 of the 46 countries, covering a large portion of all four UN Sub-Region in SSA: Eastern, Middle, Southern, and Western Africa.

4 Economic Value Concepts for Forests

The largely empirical and context specific literature reviewed above has yet to be complemented by a formal theoretical underpinning. Economic theory of forest dynamics is primarily concerned with optimal resource extraction and comparing alternative land uses (including ones that necessitate land conversion and, hence, deforestation) from the viewpoint of the forest proprietor (Angelsen & Kaimowitz, 1999; Balboni et al., 2022; Kaimowitz & Angelsen, 1998; Zhang, 2017). Recent analytical frameworks from Forestry (Jagger et al., 2022; Oldekop et al., 2021) complement it by considering alternative ways of forest managements, including community-based variants, and linking income and consumption smoothing effects (which were identified as relevant factors in the deforestation literature) to poverty dynamics.

Where the value of conservation is not deemed exceptionally high, forests are likely not left completely undisturbed. What follows is that about two thirds of the world's forests are currently used to some extent for the extraction of timber(FAO & UNEP, 2020). For sustainable forest management, it is also important how comprehensively the non-pecuniary benefits of these forests are valued. Economic theory suggests that the optimal rate of extraction from a renewable resource, like timber in a forest, may vary with the land owner's cost structure. In particular, if non-timber benefits are not properly accounted for, interest rates are high, and regrowth slow, it may be lucrative to clear a forest once and for all, and subsequently convert the land to an alternative land use (Balboni et al., 2022).

While many other factors, such as market access, openness to trade, agricultural productivity, and credit constraints play an intermediary role, it is generally acknowledged by environmental economists that the economically optimal rate of extraction tends to be higher than the forest's maximum carrying capacity. Samuelson (1976) was among the first to contend that the presence of large externalities in forestry could provide justification for the optimal forest rotation period being closer to the forester's optimum concept of maximum sustained yield; that is, socially optimal forestry might yield a larger standing forest in the steady state than is generally preferred by a sole land owner.[5]

Clearly, a more comprehensive accounting of the non-timber benefits that accrue to the people in a forest's vicinity (like NTFPs and air purification) or even on a global scale (like carbon storage) can motivate market interventions. Because ownership of forests is not always clearly defined, however, government capabilities are limited, and monitoring costs are high, such intervention is likelier to take the form of a subsidy for prudent forest management and conservation (in the form of payments for ecosystem services, or PES), rather than a Pigouvean tax on deforestation itself (Balboni et al., 2022).

In an attempt to account for all benefits of forests, the economics literature on environmental valuation has divided forest benefits in various different ways. Chief among these is perhaps that between market and non-market goods and services (else known as pecuniary/non-pecuniary or monetized/unmonetized). To assess which benefits are most unique to forests and, thereby, least likely to be compensated for by alternative land uses, a more granular classification is necessary.

Economists also distinguish between use and non-use value. Use value is the value that arises from direct use of a good, usually in context of environmental goods. It is divided into consumptive and non-consumptive use value. Consumptive use value is the value derived from consumption and depletion of a good. With regards to forests, this coincides with the "extractive" value of timber and other rival goods that are harvested. These also include NTFPs such as wild fruits, herbs, pharmaceuticals, fuel from sprigs and leafs, among others. While consumptive use value is always rival, access to it varies from excludable to non-excludable depending, *inter alia*, on land ownership and accessibility.

Non-consumptive use value, on the other hand, is the value derived from using a good that does not deplete it. With regards to forests, this includes its use for recreation as well as ecosystem services; a catch-all term for biophysical processes by which forests (and ecosystems more generally)

[5]Formal models of optimal forest rotation, with and without ecosystem services, commonly follow the optimal stopping rules first proposed by Faustmann (1849) and Hartman (1976), respectively. A generalized version of the Faustmann rule is presented by Chang (1998). For a rigorous introduction, see chapter 7 of Conrad & Rondeau (2020).

improve human well-being. These include those mentioned earlier: water cycling, air purification, suppression of disease vectors, and carbon storage to just name a few. They are entirely non-excludable and non-rival, and their scope varies from local (e.g. water cycling) thru regional (e.g. air purification) to global (e.g. carbon storage). These are the forest benefits on which the conservation discourse has largely focused in recent years, and it is the protection of ecosystem services that most payment schemes and other policy campaigns are aimed at.

Forests' non-use value arises from the environmental resources within forests, without physical interaction with those whose utility is increased by them. Non-use value can be subdivided into vicarious consumption value, bequest value, existence value (Keohane & Olmstead, 2016), and serendipity value (Banzhaf, 2019; Krutilla, 1967).

Vicarious consumption captures the non-use value from hearing about other people using a natural resource, like listening to friends stories about travelling to the Amazon. Bequest value is the often cited value of keeping the natural environment intact for future generations to enjoy and make use of. While it generally acknowledged to be a valid value concept, the weight it should be given in contemporary cost-benefit analyses is strongly contested. In economic models that aim at optimizing utility over more than one time period, utility gains that lie further in the future - including those enjoyed by one's offspring - need to be discounted due to uncertainty.

The discount rate of environment-derived future value has most prominently been contested with regards to calculating the NPV of climate change damages: While the prescriptive approach, introduced by the Stern Review on the Economics of Climate Change (Stern & Britain, 2007), proposes a conservative discount rate of 1.4 percent, the descriptive approach formulated in response to it (see Mendelsohn, 2008; Nordhaus, 2007) values future generation's bequest value at observed market rates of 3 to 5 percent. However, as the time horizon becomes ever larger and the uncertainty associated with future events compounds, this implies a certainty-equivalent discount rate should equal the lowest possible discount rate (Weitzman, 1998, 2001).

For phenomena that involve structural uncertainty and very low probability events with catastrophic results, like the complex system dependencies and tipping points characteristic of climate change, the argument can be taken to an extreme: where economic consequences of this so called "fat-tailed" structural uncertainty can readily outweigh the effects of discounting alltogether (Weitzman, 2009). The relevance of bequest value for contemporary cost-benefit analysis continues to be contested as the climate crisis continues and has gained further relevance due to the emerging twin-crisis of biodiversity loss (Dasgupta, 2021).

Existence value is the value obtained from the mere fact of knowing that something exists, even if the people in question never see it. Salient examples are large animals like polar bears, pandas, rhinos, elephants and tigers. Similar existence value may also originate from indigenous groups that live within forests or from forest ecosystems themselves.

Krutilla (1967) coined the term serendipity value to describe the inherent value that large forest ecosystems and the bioma within them hold for scientific exploration and discovery. Serendipity value is perhaps the most difficult to measure directly, given that it involves unknowns by its very definition. The existence of to date unknown substances, the pharmaceutical use of which remains to be discovered, is a common example of serendipity value.

An entire sub-field within environmental economics is dedicated to the valuation (or monetization) of environmental goods and services for which no market prices are commonly available. Most employ either Stated Preference methods, like Contingent Valuation, and Revealed Preference methods, like the Hedonic Method, to either directly or indirectly elicit peoples' willingness to pay (WTP) for a given environmental good or service (Boxall et al., 1996; see Mendelsohn, 2019). A relatively recent addition to the valuation toolbox, the Life Satistaction Approach or LSA (Frey et al., 2010) promises to be more comprehensive.

It uses Subjective Well-Being (SWB) metrics and calculates the cross-elasticities of environmental variables and income with respect to SWB to arrive at an estimate of the environmental variables' composite monetary value (Maddison et al., 2020; OECD, 2018b, 2018a; Papastergiou et al., 2023; Welsch & Kühling, 2009). LSA has found ample use in applied work, including valuation of air quality (Luechinger, 2009), flood disasters (Fernandez et al., 2019; Luechinger & Raschky, 2009), water quality (Newbold & Johnston, 2020), wind turbines (Krekel & Zerrahn, 2017), energy efficient lighting (B. A. Jones, 2018), and climate change (Dietrich & Nichols, 2023; Zapata, 2022). This paper acts as a first step towards adding the valuation of forests generally and deforestation in particular to this list.

5 Conceptual Framework

Interpreting SWB as a direct (if imperfect) measure of a given agent's utility enables the analyst to compute that agent's total value concept, from an experienced utility perspective, whereas traditional approaches are typically limited to estimate subsets thereof that are considered subject to the agent's decision utility (Kahneman et al., 1997; Kahneman & Krueger, 2006; Kahneman & Sugden, 2005). Alternatively, LSA might be used to test whether markets are out of equilibrium (Ferreira & Moro, 2010; Van Praag & Baarsma, 2005) and, if so, "to estimate residual shadow costs that could be added to implicit prices estimated using the Hedonic Method" (Holmes & Koch, 2019, p. 3).

Rather than aiming at monetizing the effects of deforestation, this study investigates the impact of deforestation experienced by a set of randomly selected individuals on their experienced well-being as measured on a Cantril (1966) Scale ranging from 0 to 10 (where higher values indicate greater life satisfaction). One reason herefore is that the focus here lies on changes in environmental conditions. In intertemporal settings like mine only the residual environmental effect on SWB can credibly be captured by LSA (Frey et al., 2010). "Compensation of [intertemporal] changes is likely to be less pronounced and the residual effect may capture a great part of the overall effect. Nevertheless, conceptually, it is still a residual effect and the LSA remains complementary to other valuation methods" (Frey et al., 2010, p. 19). Thus, I leave monetization to future research.

5.1 Subjective Well-Being

SWB refers to how people experience and evaluate different aspects of their own lives. It is frequently used to measure mental health and happiness, and it can be an important predictor of health, wellness, and longevity in individuals as well as societal health (Diener & Ryan, 2009). In addition to providing psychologists and other social scientists a way to assess how people feel about their lives, it also offers insights that can be used to evaluate public policies (Proctor, 2014). The original formulation of SWB by Diener (1984) posits that there are three distinct but related components to how people perceive their own well-being:

- Frequent positive affect, which involves experiencing positive emotions and moods on a frequent basis,
- infrequent negative affect, which means not experiencing negative feelings or moods often,
- and cognitive evaluations; this last component relates to how people think about their lives and overall life satisfaction.

According to Diener (1984), these three factors determine how people experience the quality of their lives. SWB also encompasses the emotional reactions people have and the cognitive judgments they make about their own life experiences.

SWB has become increasingly popular as a measure of overall life satisfaction, happiness, and well-being. Frequently used as a measure in psychological research and as a marker of individual health, SWB has also gained some traction among economists. Some prominent examples include the literature on the nonlinear relationship between economic growth and SWB (i.e., the "Easterlin Paradox" due to Easterlin, 1974; see also Easterlin & O'Connor, 2020; Jebb et al., 2018; C. F. Kaiser & Vendrik, 2019), well-being effects of progressive taxation (Oishi et al., 2012), its use as an alternative to more established monetary metrics of economic well-being in policy evaluations (Kahneman & Sugden, 2005; Krueger & Stone, 2014; Odermatt & Stutzer, 2017), and most recently the use of LSA for the valuation of non-market goods in environmental economics (Frey et al., 2010; OECD, 2018b; Welsch & Kühling, 2009).

In the psychology literature there exists a distinction between experienced well-being and evaluative well-being. The prior is concerned with momentary affective states and the way people feel about experiences in real-time, while the latter is the way they remember their experiences after they are over (Kahneman et al., 1999). Evaluative well-being may include individual assessments of life domains such as standard of living, housing, job, marriage, and personal health and can be considered as a subjective alternative to multidimensional indeces like the Multidimensional Poverty Index (Alkire et al., 2020; Alkire & Foster, 2011). It is often used in policy evaluation studies. On the other hand, experienced well-being seeks to bypass the effects of judgment and memory and capture feeling and emotions as close to the subject's immediate experience as possible. In this study, the focus lies on evaluative well-being as this is the type of variable that more frequently underlies the environmental valuation studies cited above (Maddison et al., 2020).

One issue that arises at a conceptual level when monetary metrics are replaced with SWB concerns measurement. SWB is most frequently elicited in surveys by use of a "Cantril's Ladder" type question (Cantril, 1966), which results in an ordinal scale rather than cardinal one. In economic theory, utility functions are assumed to be cardinal in order to ensure interpersonal comparability. Although ordinal rankings are used widely in economics, for instance in poverty analysis, this is usually done in reference to assumptions that ensure interpersonal comparability in absence of cardinality (Alkire & Foster, 2011; Sen, 1976). With SWB, on the other hand, the variable to be measured is inherently subjective, which makes comparability difficult to argue for more generally:

> Just as monotonic transformations of the utility function do not change choices under a revealed preference model of utility, monotonic transformations do not alter the category into which expressed utility or happiness falls. Therefore, unless the distribution of responses across categories enables us to conclude that one underlying distribution is greater than the other in the sense of first-order stochastic dominance, we cannot order the means. However, we will not be able to establish first-order stochastic dominance of the underlying distributions unless the estimated variances are identical, which is an essentially zero-probability event (Bond & Lang, 2019).

Bond and Lang's (2019) point is merely that regardless of how utility or happiness is elicited, one cannot know more than the ranking of happiness. This interpersonal incomparability is also known as differential item functioning (DIF). Greene (2018) cites two basic features of survey data that compound this conceptual issue further.

First, surveys "often measure concepts that are definable only with reference to examples, such as freedom, health, satisfaction, and so on. Second, individuals do, in fact, often understand survey questions very differently, particularly with respect to answers at the extremes" (p. 923). While DIF is often considered an accepted feature of the model within a given population, it can be strongly distortionary when comparing very disparate groups. In practice, this casts doubts on the many studies that make such SWB comparisons, for example across countries. Rather, comparisons based on SWB should only be made within relatively homogeneous populations and claims of external validity must be justified, for instance through the use of anchoring vignettes (King et al., 2004; King & Wand, 2007). Contrary to these methodological and theoretical concerns, a recent empirical study by van Hoorn (2018) provides evidence that DIF might be of less concern in practice than is widely accepted.

Parallel to the conceptual concerns regarding interpersonal comparability, using ordinal variables such as SWB as a response variable in statistical inference adds complexity to the model. Given that the ordinal scale is understood to be a censored reflection of the underlying (latent) utility function, a linear model might not be appropriate.

Subjective well-being ratings from zero to ten can be interpreted as a censored, ordinal transform of an underlying (latent) utility function. For any individual respondent, economists generally hypothesize that "there is a continuously varying strength of preferences that underlies the rating they submit" (Greene, 2018; C. Kaiser & Vendrik, 2020; Schröder & Yitzhaki, 2017). To see this more formally, denote utility as ranging over the entire real line:

$$-\infty < U_i^* < +\infty \tag{1}$$

where i indicates the individual. A Cantril scale with K ordered response categories maps onto the utility as follows:

$$Y_i = k \text{ iff } \mu_k < U_i^* \leq \mu_{k+1}, k = 1, \ldots, K \tag{2}$$

Thus, we observe a response category when the latent utility falls within the range defined by the two threshold parameters k and $k+1$, which are assumed to be strictly increasing in k, such that $\mu_k < \mu_{k+1} \forall k$. with $\mu_1 = -\infty$ and $\mu_{K+1} = \infty$

Using this transformation, subjective well-being can be taken to be a noisy measurement of utility - one that, unlike income or multidimensional poverty indeces, allows for a comprehensive account of what individuals value in their lives. Thus, it is (at least conceptually) capable of capturing non-pecuniary use and non-use values, including those of forests.

Estimating the effect of deforestation on SWB rather than on, say, income, offers a pathway to recovering a metric that captures direct and indirect damages that deforestation imposes on the local population, net of the immediate benefits from alternative land use and economic exploitation of extraction value. The literature on tipping points for ecosystem services, as well as the admission by economists that (at least some) forests should be considered non-renewable resources, implies that the damage from deforestation, regarding forest-related benefits, is unlikely to ever be completely compensated for by the value derived from subsequent land use.

To add to this, the non-use value of forests remains understudied and the extent of the world's forests' serendipity value, in particular, is subject to uncertainty by its very definition. The emerging hypothesis is that deforestation is likely to impose a damage on people nearby which is not reflected in monetary terms but should be accounted for when measuring utility more or less directly through SWB.

5.2 Exposure to Deforestation

There are different definitions of what constitutes a *forest* as opposed to a group of trees outside a forest.[6] Measuring deforestation in this context entails monitoring longer term changes in forest cover (FC), as opposed to daily, weekly, or monthly changes, which might result from seasonality instead of persistent land cover change (Miettinen et al., 2014; Mitchell et al., 2017).

[6] In fact the definitions of land cover types vary widely across data products, as does the extent to which they explicitly differentiate between the bio-physical land cover (like foliage, snow-cover, sand, and so forth) and its societal interpretation as land use (e.g. agriculture, built environment, etc.).

The most commonly used definition prescribes that a forest is “an area larger than 5000 m^2 (0.5 ha) which is covered 10 percent or more by tree cover, with a minimum height of 5m (FAO, 2000). Calculating the land cover change (i.e., the intertemporal difference) in a given area that complies with this definition yields a metric of forest cover change (FCC). Deforestation occurs when FCC < 0. However, the effects of deforestation on ecosystem services and, thus, on SWB in this context may not be fully encapsulated by negative FCC alone.

Rather, there exist a variety of other metrics that jointly capture the effects of deforestation more fully (Mitchell et al., 2017). They include contiguity (Seebach et al., 2013), the distance between patches of forests and non-forests (Potapov et al., 2017; Yang & Mountrakis, 2017), vegetation indices to measure plant health (Grings et al., 2020; Mashhadi & Alganci, 2022; Prăvălie et al., 2022), and contextual land cover changes in the surrounding, including the presence of built infrastructure (Silva Junior et al., 2020; Turubanova et al., 2018).

In this study, the Forest Attrition Distance (or FAD) complements FC in capturing the effects of deforestation that may not depend so much on a forest's remaining area, but rather the distances between patches of forest cover in the wider landscape. While FC tracks the area of intact forest canopy at a given location, FAD measures the euclidean distance in meters from every given pixel in an area to the closest forested pixel (for forested pixels $FAD = 0$). This metric relates to the concepts of patch size and isolation effects, according to which a landscape's ecosystem health not only depends on the area covered by intact forest but also on this area's spatial contiguity (Forman, 1997).

Higher FAD values are indicative of larger patches of non-forested areas. The metric is consistent with the habitat amount hypothesis (Fahrig, 2013) “by examining the patch isolation effect and its surrounding local landscape” (Yang & Mountrakis, 2017). Since patch isolation is an important indicator for species richness (Hanski et al., 2013), using FAD in my analysis controls for those effects on ecosystem services and other benefits related to a forest's biodiversity that depend on contiguity in addition to total area. A decline in forest density, reflected in a positive FAD change or FADC between two points in time, is a hallmark of deforestation and is conceptually related to decreasing ecosystem health.

Equipped with these two indicators, what remains to be defined is the scope at which they should be measured. Most social science studies of forest cover dynamics base their indicators at administrative boundaries of varying level (see e.g., Runfola et al., 2020), whereas papers in biology, forestry, or environmental sciences usually follow natural boundaries like those defined by biomes, biogeographic realms and the different levels of contiguous ecoregions nested within them (Olson et al., 2001; Yang & Mountrakis, 2017). These definitions remain somewhat fluid and arbitrary. In fact, administrative boundaries tend to have important ecological implications as well as social, economic, and political ones (Aslan et al., 2021; Fischer, 2018; Knight & Landres, 1998).

Aposit for capturing forest cover change over larger areas, these levels of measurement do not reflect exposure to forest cover change from people's individual, local perspectives. Considering that this paper's purpose is to investigate deforestation's local effects on SWB, exactly these perspectives need to be captured, though. Metrics based on large area summary statistics can be improved upon somewhat by population-weighting (as e.g. in Andrée et al., 2019), but this approach too runs risk of obscuring local variation in exposure at resolutions below the boundaries considered. Therefore, I propose a contrary approach to define exposure to deforestation, limiting measurement on the immediate spatial vicinity of the individuals or households in question.

Operationalizing exposure by the share of forest cover changes that occur in spatial proximity to people only, one can foresee considerable differences between the metrics this approach yields and those obtained by other means. First and foremost, forests tend to be less dense and generally less prevalent in conurbations. Thus, one would expect less forested areas and higher loss metrics, by percentage, from equally sized marginal losses in tree cover. In this study, relatively narrow circular buffers with a radius of 10 kilometers around individuals' coordinates are used to measure their exposure to deforestation.

While buffers like these have not been widely used in the literature on forest cover change, they have been used with some frequency in studies at the intersection of the policy-evaluation and GIS literatures. Examples include topics as diverse as the effects of earthquake exposure on banks' risk taking (Bos & Li, 2022), particulate matter concentrations in urban spaces (Ross et al., 2007), the design of district heating networks in built environments (Lumbreras et al., 2022), environmental effects on health outcomes and behavior in children and adolescents (Nigg et al., 2022), and the effects of urban green spaces on noise nuisance (Dzhambov et al., 2018).

5.3 Causal Model and Hypotheses

Based on the conceptual framework and literature review above, a sparse causal model emerges. Its structure is depicted in the Directed Acyclic Graph (or DAG) in Figure 3.

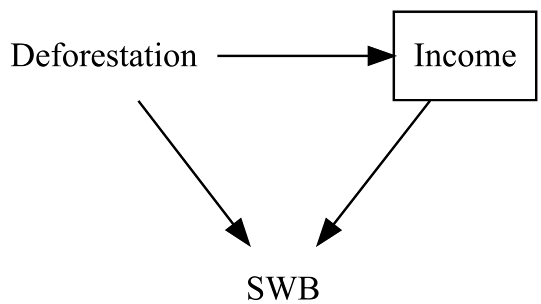

Figure 3: "DAG mapping the direct and indirect effects of Deforestation on Subjective Well-Being."

The effect of interest is the direct effect of deforestation (subsuming FADC and FCC) on SWB. Income also has an effect on SWB. If deforestation has a causal effect on income, this opens a backdoor path between deforestation and SWB whereby deforestation also affects SWB indirectly through its effect on income. This simple model yields a strategy for causal inference. Clearly, to isolate the direct effect of deforestation on SWB, income needs to be adjusted for to close the backdoor path. Thus, causal inference needs to control for income to fulfill the backdoor criterion.

Before I introduce the data and outline empirical strategy, the structure of the model summarised in Figure 3 gives rise to the following three hypotheses. First, if the non-market goods and services provided by forest ecosystems really affect people's wellbeing, the following two hypotheses should hold.

> H1: Controlling for income and other confounders, the coefficient of Forest Cover Loss (FCC) on SWB in the vicinity is negative.

> H2: Controlling for income and other confounders, the coefficient on forest attrition (FADC) on SWB in the vicinity is negative.

In addition, the literature on forest-poverty relations attests that the negative effects of deforestation are particularly stark for low-income individuals. In other words, the marginal utility of income can offset some of the marginal negative effects of deforestation. This is captured by the following hypothesis:

> H3: The direction of deforestation's total effect on SWB follows from the cross-derivative of SWB with respect to income and deforestation.

6 Data and Operationalization

The empirical exercise in this paper combines survey data on subjective well-being and its covariates with remote-sensed Land Use and Land Cover (LULC) data, from which several indicators of deforestation are derived. I briefly introduce the data sources before turning to the operationalization of deforestation.

6.1 Gallup World Poll

The survey data set used in this analysis is the Gallup World Poll (GWP), a proprietary data product produced and licensed by the American analytics and advisory company Gallup. Beginning in 2005, it continually surveys residents in more than 150 countries and areas, “representing more than 98% of the world’s adult population” (Gallup, 2021, p. 4). It uses randomly selected, nationally representative samples. Each wave, approximately 1,000 individuals per country are surveyed using a standard set of more than 100 core questions translated into the respective local language(s).[7] The survey, which is conducted once per year in most countries, takes the form of a computer assisted telephone interview (CATI) if a country’s rate of telephone ownership surpasses 80 percent, and face-to-face computer assisted personal interviews (CAPI) elsewhere.[8]

By default, the World Poll includes the following global indexes: law and order, food and shelter, institutions and infrastructure, good jobs, well-being, and brain gain. Its thematic breadth, as well as its geographic and temporal scope, have allowed for GWP to be used extensively in scientific research across multiple disciplines, including Psychology, Global and Public Health, Medicine, Agronomy, Environmental Sciences, and Economics. Table 1 contains a non-exhaustive list of empirical (some, causal) relationships studied using this data.

[7] Additionally, Gallup works with organizations, cities, governments, and countries to create region-specific custom items and indexes to gather information on specific topics of interest.

[8] More information on survey methodology and content can be found in the latest handbook, which is openly available online.

Table 1: Selected peer-reviewed publications using the Gallup World Poll.

Response Variable	Explanatory Variable	Reference(s)
food security	employment (wage-setting)	Reeves et al. (2021a)
food security	family policy	Reeves et al. (2021b)
food Security	political instability	Sousa et al. (2019)
human-nature relations	consumption technology	Richardson et al. (2022)
longevity	SWB	Evans & Soliman (2019)
mental Health	food security	Elgar, Pickett, et al. (2021), Na et al. (2019)
mental Health	vulnerability	Jorm & Mulder (2021)
subjective health	exposure to nature	Silva et al. (2018)
subjective health	GDP per capita	Deaton (2008)
subjective health	trade agreements	Liu et al. (2022)
SWB	aging, subjective health	Steptoe et al. (2015)
SWB	agroecological practices	Milheiras et al. (2022)
SWB	air pollution	Xia et al. (2022)
SWB	economic growth	De Neve et al. (2018), Deaton (2008)
SWB	food security	Smith et al. (2023), Dou et al. (2022), Elgar, Pickett, et al. (2021), Elgar, Sen, et al. (2021), Frongillo et al. (2019), Frongillo et al. (2017), A. D. Jones (2017)
SWB	GDP per capita	Deaton (2008)
SWB	gender	Joshanloo & Jovanović (2020)

Response Variable	Explanatory Variable	Reference(s)
SWB	social capital	Calvo et al. (2012)
SWB	income	Jebb et al. (2018), Reyes-García et al. (2016)
SWB	life expectancy	Deaton (2008)
SWB	religiosity	Joshanloo (2019)
SWB	state fragility	Elgar, Sen, et al. (2021)
SWB	subjective health	Joshanloo & Jovanović (2021)
SWB	SWB	Joshanloo et al. (2018)
trust in health care	GDP per capita	Deaton (2008)
vaccination coverage	trust in government	Monfared (2022)

Notes: GDP = Gross Domestic Product. SWB subsumes hedonic and eudaimonic well-being, life satisfaction and mental balance.

As demonstrated by the studies listed in Table 1, GWP often serves as a source of indicators for subjective well-being and (under)nutrition. In fact, reviews of subjective well-being (Boarini et al., 2012; Diener & Tay, 2015; Jaswal et al., 2020; Joshanloo, 2022; Reyes-García et al., 2021; Shiba et al., 2022), food security (Pereira et al., 2021; Sinclair et al., 2022; Wambogo et al., 2018) and water security (Young et al., 2021, 2022) at the national, regional, and global levels heavily rely on this data and its quality is widely acknowledged as industry leading.

The GWP contains two sections on subjective well-being. They survey evaluative and experienced well-being, respectively. For this analysis, evaluative well-being as captured by GWP's question WP16 serves as the response variable:

> Please imagine a ladder, with steps numbered from 0 at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?

In addition to this 0-10 SWB score, I retain a set of individual, household, and community level covariates to control for confounding during the analysis.

The individual level covariates include gender, age, highest completed education, marital status, employment status, respondent's religion, and dummies indicating whether the respondent was born in the country or not, owns a landline and/or mobile phone, an has access to the internet. The household variables include the household size, number of children in the household, total and per capita annualized household income in International Dollars. The community level data refer to the primary sampling unit (PSU) which the household is located in. These are approximately equivalent to a village level indicator and include dummy on whether the PSU lies in a rural or urban area, indicators of the national region, as well as GPS coordinates indicating the exact location of the PSU's centroid (to about one kilometer of accuracy). The latter are crucial for linking the World Poll data with land cover data as well as for the ensuing spatial analysis.

6.2 Land Use and Land Cover Data

While geocoded household data provides the dependent variable as well as covariates, land use and land cover (LULC) data yields metrics for deforestation. Temporal coverage remains a limitation of remotely sensed LULC data given its relatively recent history (Zabala, 2018). García-Álvarez et al. (2022) survey global general LULC datasets, noting those for which time series of maps are currently available. Their list suggests a trade-off between temporal range and resolution: The LULC products that go far back into the past tend to have a coarser resolution, while the most highly resolved maps are available only for a relatively recent, short time frame.

The LULC data for this analysis comes from Google's Dynamic World Dataset, which balances the tradeoff between temporal range and resolution relatively well. Dynamic World (DW) is a 10m near-real-time (NRT) LULC dataset that includes class probabilities and label information for nine classes of land use covering all of the planet's landmass except Antarctica. Predictions are available for the Sentinel-2 L1C satellite image collection from 2015-06-27 to present. The revisit frequency of Sentinel-2 is between 2-5 days depending on latitude and DW predictions are generated for Sentinel-2 L1C images with 35% or less of cloudy pixels. Predictions are masked to remove clouds and cloud shadows using a combination of S2 Cloud Probability, Cloud Displacement Index, and Directional Distance Transform. Further information on DW's methodology is provided in Brown et al. (2022).

For this analysis, the advantages of DW data relative to alternative LULC data sources are threefold. First, with its 10m moderate resolution, DW is among the highest resolved LULC data products that are openly available today (Brown et al., 2022; García-Álvarez et al., 2022). Therefore, it can be used to monitor very localized variation in forest cover and associated metrics, which in turn allows for more detail when aggregating over spatial units like single point buffers, administrative subdivisions, countries or regions.

Second, DW not only offers a globally coherent and comparable taxonomy of LULC classes, but also provides the underlying estimated probabilities of complete coverage by class for every single pixel. This sets it apart from other categorical LULC maps. It allows the user to customize the confidence with which a pixel belongs to a given LULC class, by thresholding on the estimated probability. Thus, in addition to the categorical map that corresponds to the highest probability in each given pixel (called Top-1 label), DW can be used to create categorical LULC maps at arbitrarily higher or lower levels of confidence, which allows the user to customize the tradeoff between confidence and variation in the data.

Third, and lastly, DW performs exceptionally well in qualitative comparison with other data sources. Its temporal and spatial coverage and moderate resolution are top of its class, and the predictive accuracy of its Top-1 probability labels is among the best in terms of expert agreement (see Table 10 in Brown et al. (2022)). DW's reliable, near-real-time classification of land cover provides opportunities for further research down the line. For example, it could be leveraged for more comprehensive analyses of the trade-offs between different land cover classes (e.g. trees versus agriculture) or to use estimated dose-response functions like the ones derived here to forecast SWB effects as new LULC data becomes available.

6.3 Operationalization of Deforestation

The analysis uses two distinct variables to capture forest dynamics: the share of an area's surface covered by forests (Forest Cover, FC) and its Forest Attrition Distance (FAD). They are first computed for each pixel on a grid and then aggregated through circular buffers with a 10 km radius around each interview location. To measure change in a forest's structure over time, "recall" and "reference" periods are defined relative to each interview date d_i. The recall period starts $\tilde{d}$ days before d_i and ends on d_i. The reference period is set to precede the recall period by a year, thus stretching from $d_i - 365 - \tilde{d}$ to $d_i - 365$. The timing is depicted graphically in Figure 4, along a line signifying a discrete date count $-\infty \leq d \leq \infty$.

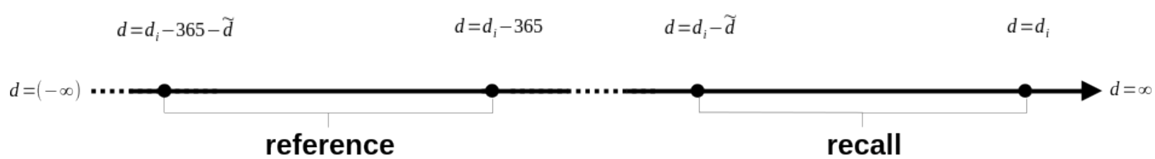

Figure 4: Timing of reference and recall periods of length $\tilde{d}$, one year apart.

Changes in FC and FAD (denoted as FCC and FADC, respectively) are calculated by comparison between the reference and recall periods. This process of seasonal differencing prevents the results from mistaking seasonal or otherwise naturally cyclic LULC changes for persistent, anthropogenic ones (Miettinen et al., 2014) and aligns the temporal periodicity of the DW data with that of the GWP data.

The steps needed to process the DW data and obtain FADC and FCC can be divided into grid operations, whereby a raster of pixels is manipulated so that it yields new variables, and point value extraction, which is the process of assigning an aggregate value from a two-dimensional pixelated raster image to a point on that same grid. Point value extraction links the spatial data to the survey date in the GWP and, thereby, makes it usable for the analysis. Figure Figure 5 schematically summarizes the spatial data processing at the pixel level, while Figure 6 shows the extraction process.

On top of Figure 5, the GW data enters the process. First, the tree cover percentage band is selected; This band of DW includes the estimated probability that a given pixel on a given day is entirely covered by trees. The probability band is then reduced to the mean of tree cover probability $E(P(T))$ for each pixel during, both, the reference and recall periods. After pixels covered by water are masked out in step three, the probability band yields two maps that show how the mean probability of tree cover is spatially distributed. These mean probability maps are recoded to binary maps indicating $\mathbf{1}(E(P(\text{trees = 100 }\%)) \geq \tau)$, that is whether a pixel's value lies below or above a threshold τ. Pixels with a mean probability below τ receive a zero, while probabilities at or above τ are coded as ones, yielding a simple indicator of tree cover versus non-tree cover.

The choice of probability threshold τ is similar in nature to that of tuning parameters in the statistics literature on false discovery rates. The higher τ, the more pixels are classified as covered by trees and vice versa. Thus, as $\tau \rightarrow 0$, the resulting metric overstates the actual extent of tree cover in any given neighborhood of pixels. On the other hand, as $\tau \rightarrow 1$ the condition for tree-cover classification becomes overly restrictive and virtually no tree cover is detected. In practice, $\tau = 0.33$, in combination with the forest definition discussed below, has yielded close agreement with another existing forest-nonforest map at lower spatial resolution (JAXA, 2022). That specific threshold is applied in this study, to neither over- nor underreport exposure to deforestation.

According to the FAO (2000) definition, only clusters of trees that cover an area larger than or equal to 5 hectares are considered forests. This definition is operationalized by requiring that every tree-covered pixel's 4-connected neighborhood include at least 49 other tree-covered pixels. This step is crucial as it prevents overestimation of forest cover in a given area, and as a result ensures

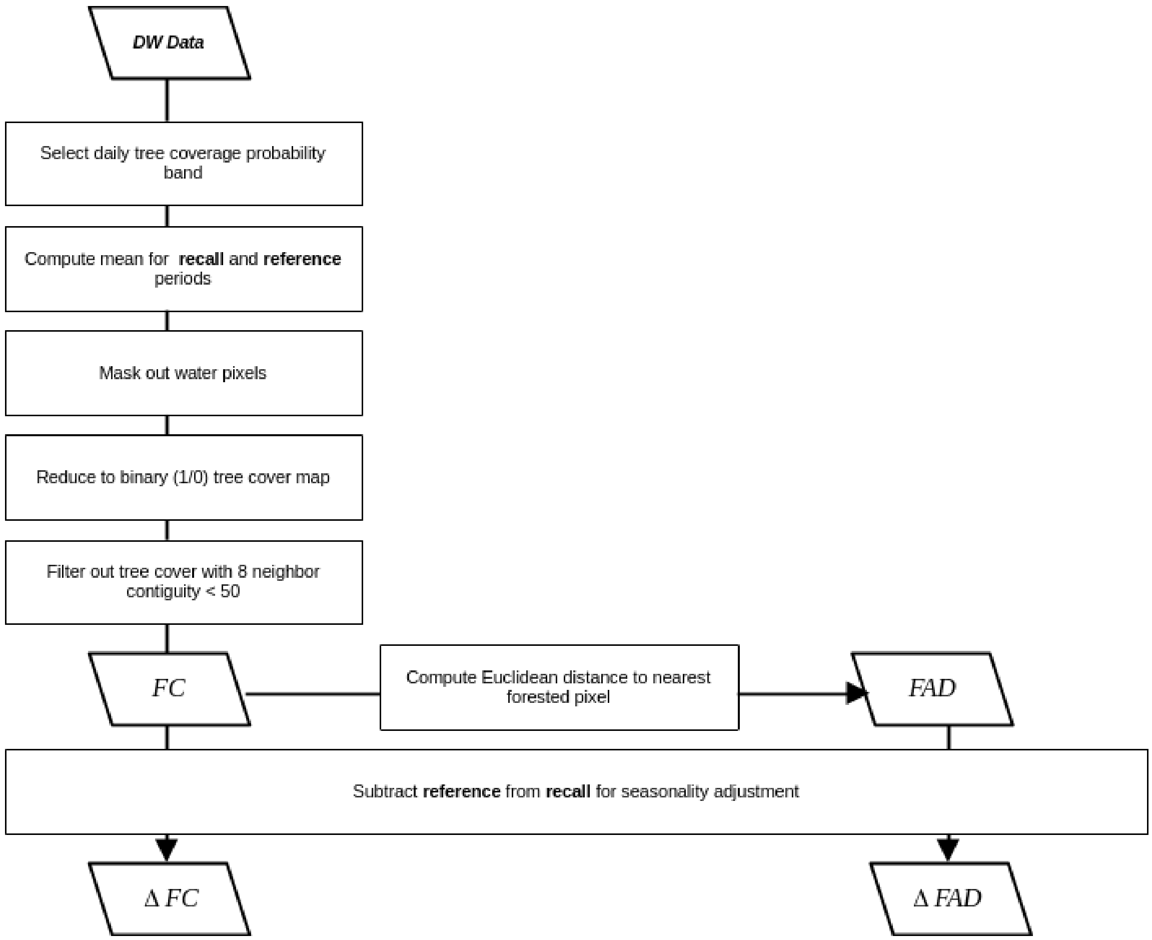

Figure 5: Data processing of Google Dynamic World (DW) data at the pixel level.

consistent estimation of forest cover change. It uses the FAO's forest area requirements in a way similar to other enhancement strategies for post-classification change detection (Seebach et al., 2013).

At Dynamic World's 10×10 meter resolution, neighborhoods of 50 pixels or more equate to an area of at least 5 hectares. In this context, a 4-connected (or Von Neumann) neighborhood consists of pixels that touch one another at one of their edges and, therefore, its pixels are connected horizontally and vertically. Importantly, this excludes those pixels that touch at their corners and connect diagonally, as in 8-connected (or Moore) neighborhoods (compare figure 1 in Yang & Mountrakis, 2017). Tree-covered pixels outside large enough neighborhoods are filtered out and recoded as zero, thus transforming the binary tree-cover maps into forest/non-forest maps.

On these forest/non-forest maps, each pixel's Euclidian distance to the next forested one is calculated; forested pixels' own distance is set equal to zero. This yields mean FAD maps for both the reference and the recall periods in line with FAD's definition given in Yang & Mountrakis (2017).

The last step of the grid processing is to difference the forest/non-forest and FAD maps. To derive forest cover loss indicators, I compare the recall and reference periods' forest status in each pixel. Pixels that moved from forest to non-forest status are coded 1, while all other pixels receive a zero, thus yielding a loss/non-loss map. To calculate mean FAD change, I subtract mean FAD during the reference period from the same metric during the recall period.

Finally, the FC, FAD, FCC, and FADC are aggregated to each interview's location. For FAD and FADC, this is done by computing their mean within a circular buffer with a radius of $r = 10$ km around the interview location, weighted by each pixel's area share of the buffer's total area of $\pi \times r^2$. To compute FC in the recall and reference periods, I sum the area of all forested pixels which intersect with the circular buffer, which includes sections of pixels along the buffer's boundary. Similarly, FCC is calculated by summing up the 10×10 m^2 surface areas of those forest loss pixels that intersect with the circular buffer, including pixel sections along the buffer's boundary.

Figure 6 depicts this aggregation process. In it, the three dimensional (latitude, longitude, time)

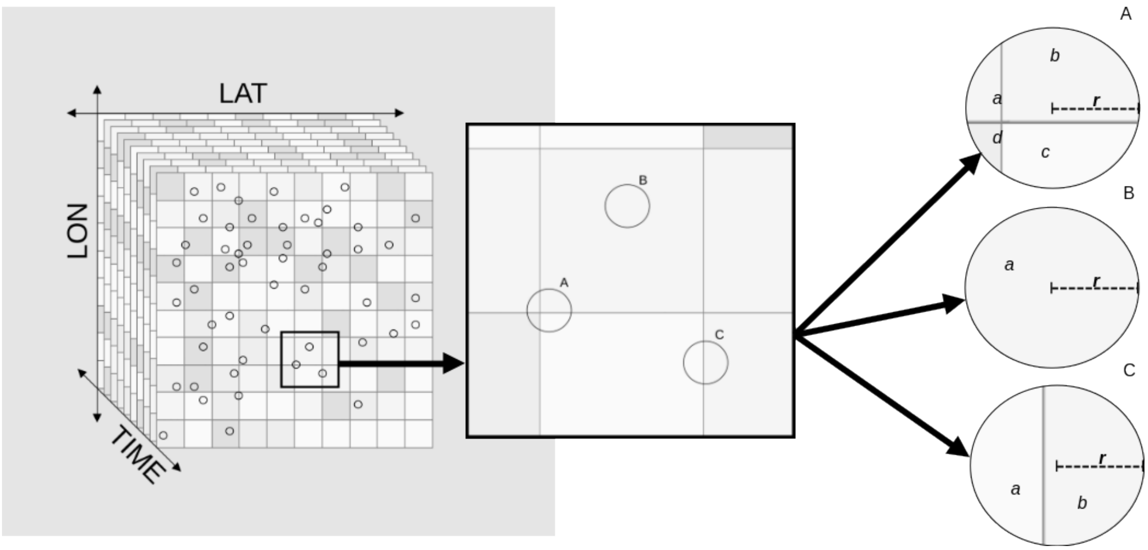

Figure 6: Extracting values at interview location, using area-weighted mean of pixels inside a circular buffer with radius *r*.

raster stack, with the circular buffers superimposed, is depicted to the left. Following the arrow to the right, the graphic zooms in to the framed rectangle in, a section of the raster where interview locations A, B, and C are located. Zooming in further still shows the circular buffers around these three locations with more detail. Note that the surface of the buffers is comprised by sections of the pixels that they lie on. Each household is assigned the weighted mean of the cell values that form part of its buffer's area, where the weights are defined by the fraction of the buffer's surface comprised of the respective pixel segment. For instance, FAD for household i is extracted as

$$FADC_i = \sum_{p \in \mathcal{P}_i} FADC_p \frac{\mathsf{A}(p \cap \mathcal{P})}{\mathsf{A}(\mathcal{P})}.$$

where p indexes the pixels on which i's buffer $\mathcal{P}_i$ lies, and $\mathsf{A}(\cdot)$ denotes the surface area. Since $\mathcal{P}_i$ is a circular buffer, the fraction's denominator is equal to πr^2, r being the buffer's radius. To the right end of panel 2 in figure Figure 6, interview A's buffer consists of differently sized sections (*a*, *b*, *c*, and *d*) and is therefore assigned a value equal to the weighted average of these four components.

Because interview B's buffer lies entirely within one pixel (which becomes increasingly unrealistic as r becomes larger), it is assigned that pixel's value. Interview C is assigned the weighted average of the two pixel sections (*a*, *b*) within its buffer's area. Note that, holding spatial resolution constant, the number of cell segments that are averaged in the circular buffers increases in r.

The mathematical operations used in the construction of the exposure variables, first pixel-wise on the grid followed by buffer-wise aggregation, are listed below in Table 39 and Table 40 in Section 11.7 in the appendix.

7 Empirical Strategy

The econometric model used to estimate the impact of deforestation in people's proximity on their SWB largely follows the standard empirical approaches proposed for the quantitative analysis of subjective well-being and satisfaction data (Ferrer-i-Carbonell, 2002; Ferrer-i-Carbonell & Frijters, 2004; Maddison et al., 2020; OECD, 2018b; Praag & Ferrer-i-Carbonell, 2008; Riedl & Geishecker, 2014).

Much of the methodological discourse in this field has focused on whether or not statistical procedures, which are originally designed for the analysis of cardinal response variables, can be relied on when dealing with ordinal SWB survey responses instead. This problem is both conceptual and statistical in nature. Ferrer-i-Carbonell & Frijters (2004) note that "psychologists and sociologists usually interpret happiness scores as cardinal and comparable across respondents," while "economists usually assume only ordinality". Due to their concerns about interpersonal comparability and violating the homoscedasticity assumption that underlies OLS, economists tend towards using ordered latent response models like ordered logit and probit rather than linear models when working with SWB as a response variable.

In its guidelines on measuring SWB, the OECD argues that, in practice, "treating ordinal data as cardinal does not generally bias the results obtained" (2013, p. 174). This advice draws onan influential paper by Ferrer-i-Carbonell & Frijters (2004), which finds that "assuming cardinality or ordinality [...] is relatively unimportant to results" (Ferrer-i-Carbonell & Frijters, 2004, p. 655). What matters more, they contend, is how one takes account of time-invariant unobserved heterogeneity through the by using the within estimator - an option that is largely unavailable for ordered Logit or Probit, in part, due to the incidental parameters problem (Lancaster, 2000; Neyman & Scott, 1948) that arises when including fixed effects in nonlinear models.

Because the data structure of the GWP follows a time series of cross sections (repeated cross sections) and the primary sampling units (PSU) are re-sampled each wave, constructing a pseudo-panel (see Deaton, 1985) is not an option. With individual fixed effects thus unavailable, the estimation strategy evolves around ensuring that higher level unit and time invariant unobserved heterogeneity does not confound the analysis. I gradually expand the range of control variables, time and region fixed effects included in the following unobserved effects model:

$$y_{ipat} = \mathbf{x}'_{ipat}\alpha + \omega_a + \zeta_t + \varepsilon_{pt} \tag{3}$$

where i, p, a, and t index individual respondent, PSU, first level subnational adminstrative area (Admin-1), and year of the survey response.

The full model contains Admin-1 and Year fixed effects, denoted by ζ_a and ω_t respectively, and regresses $\mathbf{x}_{ipat}$ on the response variable y_{ipat}, which denotes SWB (0,10). $\mathbf{x}_{ipat}$ includes Forest Cover Loss (FFC_{pt}) and Mean Forest Attrition Distance Change ($FADC_{pt}$). Considering their cross-dependency, which is demonstrated in (Yang & Mountrakis, 2017) and qualitatively replicated in Figure 9, I also include their interaction term. x also includes the respondent's gender, age, urbanicity status, and log income per capita. ⍰_{pt} is the idiosyncratic error term, clustered for Admin-1 units (Abadie et al., 2023; Liang & Zeger, 1986).

While the circumstantial evidence of Ferrer-i-Carbonell & Frijters (2004) has been subject of criticism from theoretical viewpoints (Bond & Lang, 2019; Schröder & Yitzhaki, 2017), subsequent simulation studies provide comparative evidence on the finite sample properties of OLS and its nonlinear alternatives for ordinal discrete response variables. They find that the prescriptions of Ferrer-i-Carbonell & Frijters (2004) and the OECD (2013) hold for both binary (Hellevik, 2009) and multivariate ordinal cases (Riedl & Geishecker, 2014). In extension, the benefit of eliminating unobserved heterogeneity through the fixed effects included in Equation 3 likely outweighs any potential caveats due to the response variable's ordinal nature.

The evidence presented in Ferrer-i-Carbonell & Frijters (2004) has been criticized as too narrow in scope, investigating the robustness of empirical relationships of one given well-being scale (0–10) to only a selected few econometric models (Bond & Lang, 2019; Schröder & Yitzhaki, 2017). They do not, however, proof robustness of the results to monotonic increasing transformations of the well-being scale more generally. Schröder & Yitzhaki (2017) provide a counter argument by two conditions under which it is possible to reverse the rankings of SWB means among groups and, subsequently, the signs of OLS regression coefficients. When the ordinal variable is not robust to monotonic increasing transformations of this kind, their result cautions against the use of OLS because the sign and magnitude of coefficients are affected.

It is worth noting that the theoretical concerns above have been largely discarded by the empirical literature, with C. Kaiser & Vendrik (2020) going as far as to suggest that "reversals by either relabelling or by using Bond & Lang's approach are impossible or implausible for almost all variables of interest". Nonetheless, I estimate an alternative specification of Equation 3 by conditional logit with random effects to address any doubts that might remain about potential shortcomings of OLS in the context of estimating SWB effects - the model output can be found in @sec-ologit in the appendix. In line with Ferrer-i-Carbonell & Frijters (2004), I find that assuming ordinality or cardinality of happiness scores makes little difference, whilst allowing for fixed-effects does change results substantially.

8 Summary Statistics

The maps in Figure 7 display the spatial distribution of mean SWB in SSA at three different resolutions in 2016-2019. At the country level, SWB is higher on average in Western Africa, particularly Benin, Côte d'Ivoire, and Ghana, while the Central African Republic in the continents middle, and Burundi, Malawi, Rwanda, and South Sudan and Zimbabwe in its east display the lowest well-being statistics. Disaggregating the national average to the Admin-1 level reveals a more differentiated image with considerable subnational heterogeneity. Of the ten Admin-1 units with the highest SWB, four are located in Benin, two in Côte d'Ivoire and Kenya respectively, and one each in Burkina Faso and Ghana. The ten lowest ranking Admin-1 units can be found in South Sudan (4), Malawi, Rwanda (2 each), Burundi and the Central African Republic (1 each). The highest mean SWB for any Admin-1 unit in the sample, at 7.9, was measured in Côte d'Ivoire. On the other hand, the lowest mean SWB, measured in a western district of South Sudan, was 1.6.

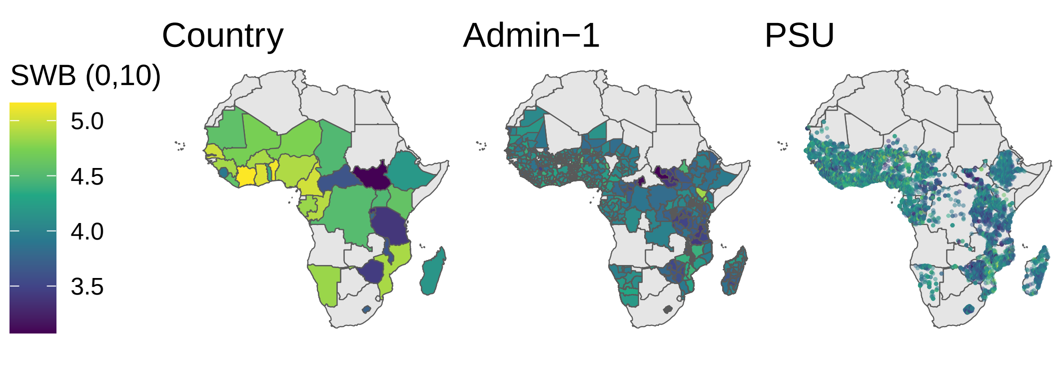

Figure 7: Spatial distribution of Mean Subjective Well-Being among Countries, Admin-1 areas, and Primary Sampling Units in SSA.

Figure 8 shows how SWB evolved over time in the four UN Sub-Regions of the SSA region. Mean SWB in all sub regions increased over the study period. Eastern Africa is consistently ranked last while Middle and Western Africa contend for the highest average SWB and Southern Africa oscillates between relatively high and relatively low SWB levels. The less opaque lines in the graph uncover once again the heterogeneity within these groups. For example, South Sudan, Malawi, Rwanda and Zimbabwe are considerably below the regional average SWB in Eastern Africa. Southern Africa's oscillation, on the other hand, can be explained by a decrease of SWB in Lesotho, which runs counter to the regions overall upward sloping trajectory.

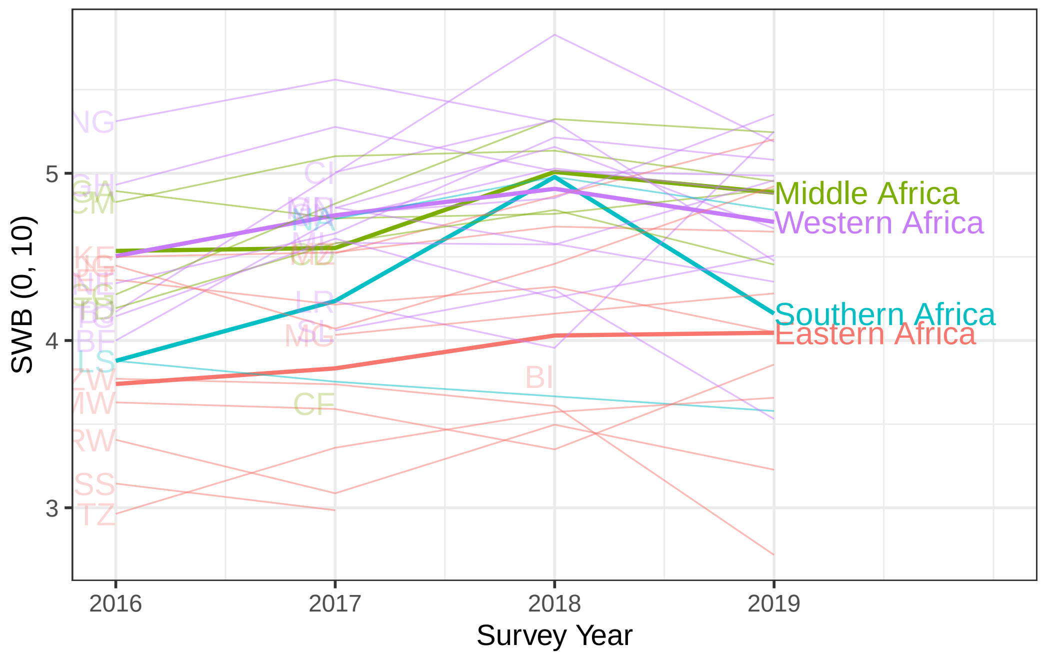

Figure 8: Subjective Well-Being over time in SSA.

As shown above, there is considerable regional, national, and subnational variation in SWB. The same is true to varying degree for all other variables from the survey data. In the interest of conciseness, summary statistics for all the variables retained from GWP are relegated to Table 6 in the appendix. Let us now turn to the exposure to deforestation metrics, and their relation to SWB. Table 2 summarises the exposure to deforestation variables for all three recall lengths $\widetilde{d} = \{30, 90, 180\}$.

It can be seen that as the recall period gets longer, less missing values occur. This is due to the lower concentration of missing pixels (due to cloud coverage, sensor malfunction, etc) over longer time periods, which are averaged within each buffer. Cloud coverage is particularly pronounced over the humid tropics, and much of SSA lies within this geographical zone. Moreover, forests are more likely to be covered by clouds than non-forested pixels, which explains why mean FC tends to increase as the recall gets longer; out of the pixels that are missing at shorter recall lengths, many are indeed forested ones.

Thus, the longest recall period considered (i.e. 180 days) seems to produce the most coherent deforestation exposure variables. For this reason, I use this set of indicators in the statistical analysis in Section 9 and relegate those based on shorter recall periods to the appendix, specifically Section 11.8.3.3.

Table 2: Summary statistics for forest variables by recall period

Recall (days)	30, N = 100289	90, N = 100289	180, N = 100289
FC Before	9 (1, 54)	23 (2, 82)	34 (4, 109)
Unknown	32,407	18,636	15,391
FC After	10 (0, 53)	26 (2, 88)	34 (4, 110)
Unknown	32,407	18,636	15,391
FCC	4 (0, 18)	6 (1, 20)	6 (1, 17)
Unknown	32,407	18,636	15,391
FCC (%)	55 (26, 93)	34 (16, 68)	22 (10, 46)
Unknown	40,681	24,918	20,584
Mean FAD Before	700 (231, 1,181)	482 (146, 1,062)	350 (95, 893)
Unknown	39,248	23,824	19,921
Mean FAD After	659 (218, 1,164)	431 (135, 1,001)	343 (99, 871)
Unknown	39,961	23,985	20,014
FADC	0.00 (-0.19, 0.18)	0.00 (-0.13, 0.09)	0.00 (-0.07, 0.06)
Unknown	44,072	26,013	21,108
FADC (%)	1 (-32, 41)	-2 (-30, 31)	-1 (-21, 26)
Unknown	44,072	26,013	21,108

Figure Figure 9 plots forest attrition distance (change) on the y-axis against forest cover (change) on the x-axis. Panel A depicts their relation in levels, thus using FAD and FC. Panel B, on the other hand, investigates the relationship between the intertemporal change variables FADC and FCC. Note that FC and FCC are expressed in percentage of the total area within a radius of 10k around the respondent's location, i.e. the circular buffer.

Yang & Mountrakis (2017) evidence a highly nonlinear relationship between FAD and FC for the case of the continental US. In highly forested areas, FAD is typically very low. As the percentage of forest cover decreases though, FAD first stays relatively constant, before increasing exponentially. The scatter plot in panel A of Figure 9 replicates figure 4 of Yang & Mountrakis (2017) and suggests that the same nonlinearity exists in SSA.

FAD only increases slowly as forest cover decreases from 100% to about 20%. From this point onwards, though, FAD suddenly spikes as forest cover further declines towards 0%. This replicated finding underpins the validity of the approach to measuring exposure to deforestation employed in this paper. Panel B in Figure 9 suggests that the nonlinearity of the level metrics does not carry over to measures of change such as FCC and FADC. Figure 12 and Figure 13 in the appendix disaggregate this graphical analysis by year and show the graphs for different recall period lengths.

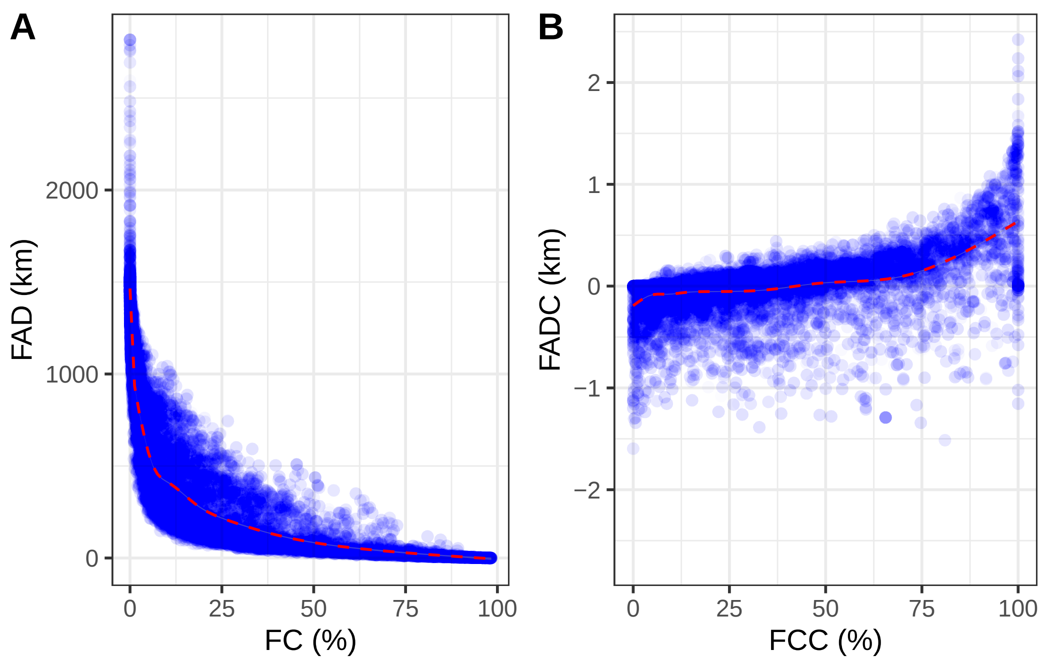

Figure 9: Scatterplots of Forest Attrition Distance (Change) and Forest Cover (Change), with LOESS fit.

Figure 10 shows how the deforestation exposure metrics are distributed spatially across SSA. It maps them aggregated to more than 600 first tier sub-national administrative (Admin-1) areas. Once more, it shows that the prevalence of extreme values decreases with longer recall periods. Regardless of the recall period, it appears that there are some specific hotspots in SSA, where exposure to deforestation is higher than elsewhere, especially in Western Africa. Out of the ten Admin-1 areas with the highest recorded forest cover loss in the sample, five are located in Côte d'Ivoire, four in Liberia, and one - with the single highest value - in Nigeria.

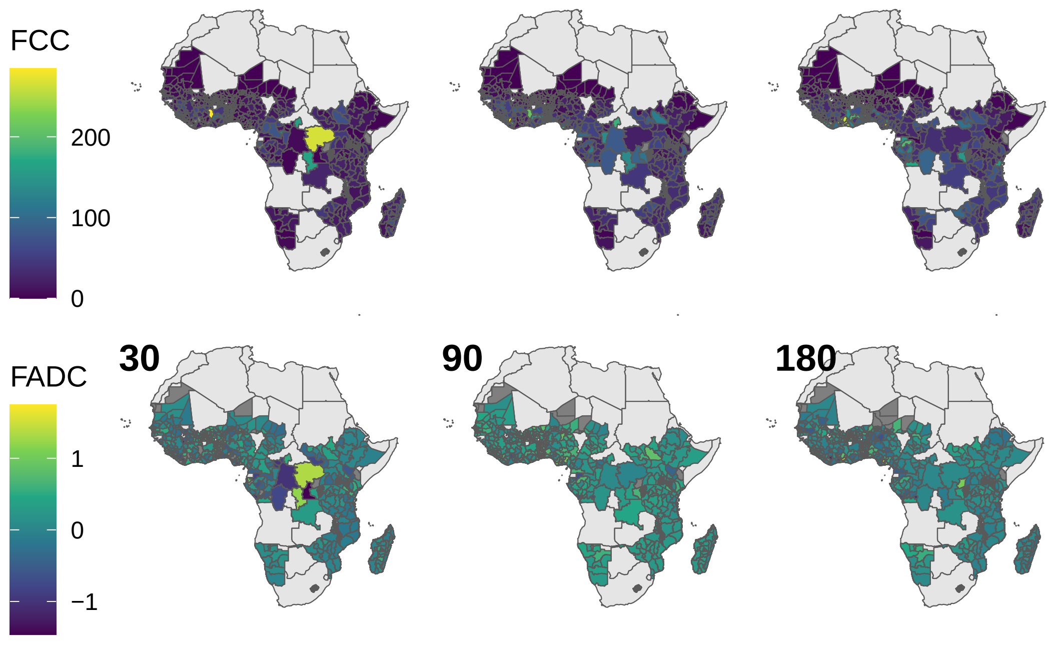

Figure 10: Spatial distribution of exposure to deforestation metrics among Admin-1 areas in SSA.

9 Results

The regression results in Table 3 come from a set of increasingly complex pooled regression models, which serve as a baseline. Complexity is increased by expanding the range of control variables (subsumed in vector **x** in Equation 3) in columns (1) thru (3) and by applying admin1 and year fixed effects(ω_a and ζ_t, respectively, in Equation 3) in columns (4) thru (6). In the model presented in column 6, income is added as a covariate to investigate whether a substitution effect between income and deforestation-related damages to SWB can be evidenced.

Table 3: OLS Regression of SWB on Deforestation Indicators.

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	4.488***	4.673***				
	(0.021)	(0.041)				
FCC	−0.004***	−0.003**	−0.003**	−0.002*	−0.002*	−0.002+
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FADC	−0.328***	−0.268***	−0.250***	−0.011	−0.001	−0.024
	(0.068)	(0.065)	(0.066)	(0.073)	(0.074)	(0.074)
FCC × FADC	0.007***	0.006***	0.006***	0.002	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		−0.014***	−0.013***	−0.011***	−0.011***	−0.010***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender [Female]		−0.142***	−0.138***	−0.004	−0.001	0.054*
		(0.023)	(0.023)	(0.022)	(0.022)	(0.022)
Urbanicity [Small Town]		0.347***	0.355***	0.167***	0.171***	0.126***
		(0.037)	(0.037)	(0.038)	(0.038)	(0.038)
Urbanicity [Large City]		0.816***	0.821***	0.339***	0.341***	0.233***
		(0.045)	(0.045)	(0.058)	(0.058)	(0.060)
Urbanicity [Suburb]		0.571***	0.559***	0.318***	0.306***	0.222***
		(0.054)	(0.054)	(0.061)	(0.061)	(0.063)
Log Income						0.164***
						(0.009)
Num.Obs.	76 537	76 537	76 537	76 537	76 537	72 285
R2	0.002	0.019	0.020	0.084	0.084	0.084
R2 Adj.	0.002	0.019	0.020	0.076	0.076	0.076
R2 Within			0.019	0.005	0.005	0.010
R2 Within Adj.			0.019	0.005	0.005	0.010
AIC	375 803.5	374 493.9	374 441.2	370 534.1	370 503.5	349 160.6
BIC	375 840.5	374 577.1	374 552.2	376 405.0	376 402.2	354 986.0
RMSE	2.82	2.79	2.79	2.70	2.70	2.68
Std.Errors	by: ea	by: ea	by: ea	by: ea	by: ea	by: ea
FE: year			X		X	X
FE: adm1				X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

SWB (0-10), FC (km^2), FADC (km), full sample of pooled cross-sections.

All of the models in the table feature negative coefficients on FCC. Columns (4) thru (6), which control for fixed effects do not yield statistically significant coefficients on FADC, suggesting that forest attrition has no discernible effect on SWB. The interaction between the two exposure to deforestation variables is insignificant as well in columns (4) thru (6).

Age is estimated to have consistently negative effects on SWb throughout all models, while urban dwellers have higher SWB on average. Gender effects dissipate once fixed effects are introduced, suggesting that some other unobserved variables better explain differences between male and female respondents.

Regarding fit statistics, neither of the models presented in Table 3 is particularly powerful; With the highest R^2 statistic of 0.081, column (5) only explains about eight percent of the data's variability.

According to the preferred specification, summarized in column (5), a 100 square-kilometer loss in forest area is associated with a 0.22 decrease in SWB. By linearity, this gives a coefficient of -0.002 for each cleared square-kilometer within a person's 10 km buffer. At the sample average of FCC (15.1 km^2), this is equal to a change of -0.03 decrease in SWB, while it amounts to -0.08 at the 90th percentile of FCC (36.73 km^2).

It is not clear whether this linearity assumption is appropriate, however. Rather than linearly, the treatment could enter in polynomial form or through and otherwise (piece-wise) nonlinear function. Therefore, I rerun the model of column (5) in Table 3. The second and third degree polynomials do not return statistically significant results, and using a cubic B-spline of FCC with knots at its 25th, 50th and 75th percentile is only borderline statistically significant at $p \leq 0.90$. Thus, there is little evidence for nonlinearities in how SWB responds to changes in forest cover - see Section 11.8.1 in the appendix for more information.

Given that the nonlinear specification is only barely statistically significant and does not improve the model fit substantially, I continue the analysis based on the preferred, linear specification. In column (6) of Table 3, log income per capita enters the model. Its coefficient is both highly significant at the 0.01% confidence level and relatively large. According to this model, a one percentage point increase in income is associated with an increase of 0.16 units on the SWB scale. Although income, thus, seems to have a significant effect on respondents' SWB, the coefficient on FCC remains significant and retains a similar effect size to the model without income. Thus, income does not seem to considerably affect the effect size of forest cover loss and, most importantly, does not change its direction to positive. This suggests that income and forest benefits are not, in fact, substitutes but complement each other to a large degree in their impacts on SWB.

The maps in Figure 11 plot the spatial distribution of the negative effects of forest cover loss on SWB across countries and Admin-1 units. These can be thought of as the marginal damages inflicted by forest cover loss in terms of the SWB scale from 0 to 10 rather than in monetary terms.

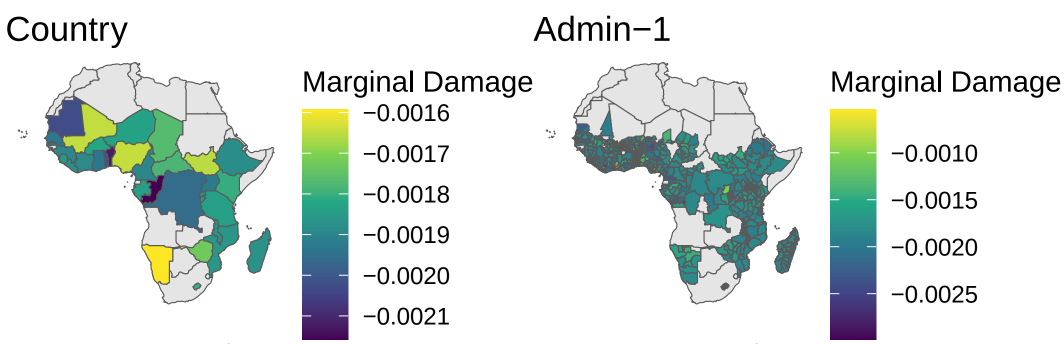

Figure 11: Spatial distribution of marginal damages of forest cover loss (FCC) in SSA.

Given that the comparability of SWB statistics across country borders is contested, I also run the models above each individual UN Sub-region and country sub-sample. The results can be found in the appendix. To summarize them nonetheless, the estimates point towards considerable heterogeneity between countries. Disaggregation at the regional level shows that FCC has statistically significant negative effects in Western and Southern African countries, while FADC is only statistically significant, and negative in sign, for Eastern Africa.

At the country level, FCC is significant in Burundi, Madagascar, Ghana, Burkina Faso, Liberia, Chad, and the Republic of the Congo, with all but Burundi and the Congo displaying negative effects. FADC, on the other hand, is significant for Ethiopia, Togo, Liberia, the Republic of the Congo, and Uganda. With the exception of Togo, all of them exhibit a negative association between forest attrition and SWB. The exact model output can be seen in Section 11.8.3 in the appendix. To summarize, there is some limited evidence of systematic negative effects of forest cover loss on subjective well-being in the pooled data, but disaggregating it to the country level reveals both positive and negative effects across different polities.

10 Conclusion

This study set out to quantify the local effects of deforestation on people exposed to it. Regressing respondent's SWB on novel metrics of deforestation exposure, defined through spatial contiguity and vicinity, yields some significant findings which seem relevant for the broader policy nexus surrounding deforestation. The primary finding of this study is that forest cover loss induces a decline in SWB. Controlling for income does not seem to affect the effect size. This finding suggests that, in the context of Sub-Saharan Africa, increases in income do not substitute for the negative effects of deforestation on other domains of people's lives. This may reflect inequalities in land ownership, as a consequence of which returns to land conversion are highly concentrated and do not accrue to the bulk of the population. Moreover, a significant share of the forest benefits typically enjoyed by people are not marketed and, therefore, cannot be easily purchased through an alternative source once the forest has been destroyed. In the end, this means that deforestation involves a persistent damage to people's well-being by depriving them of ecosystem services they had previously enjoyed and which they cannot subsitute for. As a corollary, there is no evidence to suggest the existence of an Environmental Kuznets Curve for deforestation in the local context.

Adding a cubic B-spline of the main explanatory variable (i.e. area of deforested land within the buffer) to the baseline model yields only borderline significant results. If one is willing to accept these low confidence findings, the dose-response function would seem to be signiciantly non-linear and concave as depicted in Figure 14 in the appendix. This finding would add both urgency and optimism to the policy discussion; the growth rate of SWB damages from deforestation accelerates with each additional increase in deforestation but this also points at an opportunity to prevent deforestation's worst effects by curbing it from an early stage. Once again, though, the non-linear dose response function constitutes a low confidence result and should be considered accordingly.

Overall, the findings of this study add to the broader policy-relevant discourse surrounding deforestation. They show that the powerful global incentives to curb deforestation to mitigate climate change are complemented by local negative externalities on people's subjective well-being. This new dimension may help tip the scales in favor of more effective conservation and reforestation policies. It may be of particular relevance to polities, whose leaders have in the past opted to limit or halt conservation efforts in the name of local socioeconomic development and in spite of pleas to the contrary by the science community, other state and non-state actors, and civil society at large.

As for limitations, there are several apparent in this study. On a technical level, the following are noteworthy. First, the choice of the probability threshold used to categorize pixels as either tree-covered or not is based on visual inspection of a limited number of study areas. A more systematic way of choosing the parameter τ could be used, for instance by comparing the type-1 and type-2 error rates across values of τ in comparison to existing (lower resolution) forest maps on a global or continental scale.

Second, the choosing the length of the recall period $\tilde{d}$ comprises a similar trade-off problem. Whereas I chose three arbitrary values - 30, 90, and 180 days - to explore the effect of variation in this parameter on deforestation metrics, it would be more rigorous (and computationally expensive) to evaluate the marginal effects of a change in $\tilde{d}$ in days more generally. Both these issues could also be ameliorated by using an entirely different change detection algorithm to monitor deforestation. The Breaks for Additive Season and Trend (BFAST) algorithm Verbesselt et al. (2022), for instance, can detect abnormal changes within newly acquired data based on a model for stable historical behaviour.

Third, while the fixed effects included in the regression model do eliminate unobserved and year and Admin-1 area invariant heterogeneity, problems might still arise from omitted variables that vary below the year or admin1 temporal or spatial levels. Unfortunately, more rigorous identification strategies based on within individual variation (e.g. Difference in Differences) are largely unavailable in the repeated cross-sections case with repeated sampling. Endogeneity problems, on the other hand, could be addressed using an instrumental variable. Finding a suitable instrument, which should be strongly correlated with deforestation and unrelated to SWB at the same time, can lead the way to new, interesting research capable of validating or rejecting the results presented here. Timber prices, for example, might provide a viable instrument, assuming that the revenue from timber sales and related benefits do not generally accrue to the people in a forest's immediate surrounding. Whether or not this assumption is valid for a given context, though, must be judged case by case.

On a conceptual level, the inter-personal comparability of SWB indicators like the one used in this study remain contested, not to speak of comparability across national borders. Therefore, the pooled regression results might warrant more skepticism than the country-wise regression results that accompany them (see Section 11.8.3.3 in the appendix). Either way, external validity should be tested in subsequent studies, both in SSA and beyond, to reveal the full potential of this local approach to evaluating people's exposure to deforestation. A natural extension would be to also perform a valuation of the implied damages in monetary terms, for example using the Life Satisfaction Approach. Lastly, more context-specific country case studies are necessary to complement comparative studies like this one and make sense of the heterogeneous effects of deforestation on SWB among different countries from a more integrated causal perspective.

11 Appendix

11.1 Abbreviations

Table 4: List of abbreviations and their meanings.

Abbrev.	Meaning	Abbrev.	Meaning
Admin-1	First Tier Sub-national Administrative Area	m	Meter
CATI	Computer Assisted Interviews	NPV	Net Present Value
DIF	Differential Item Functioning	NRT	Near Real Time
DW	Google Dynamic World	NTFP	Non-Timber Forest Product
FAD	Forest Attrition Distance	OECD	Organization for Economic Cooperation and Development
FAO	UN Food and Agriculture Organization	OLS	Ordinary Least Squares
FC	Forest Cover	PES	Payment(s) for Ecosystem Services
GDP	Gross Domestic Product	PSU	Primary Sampling Unit
GIS	Geographic Information System	SDG	Sustainable Development Goal
GPS	Global Positioning System	SSA	Sub-Saharan Africa
GWP	Gallup World Poll	SWB	Subjective Well-Being
km	Kilometer	UN	United Nations
LSA	Life Satisfaction Approach to Environmental Evaluation	US, USA	United States of America

Abbrev.	Meaning	Abbrev.	Meaning
LULC	Land Use and Land Cover	WTP	Willingness to Pay

11.2 Countries Included in This Study

Table 5: Countries and UN Sub-regions in the sample, by year.

Group	Country	2016	2017	2018	2019
Eastern Africa	country				
	Burundi	0 (0%)	0 (0%)	880 (9.0%)	0 (0%)
	Ethiopia	840 (12%)	1,000 (11%)	1,000 (10%)	2,222 (22%)
	Kenya	840 (12%)	944 (10%)	992 (10%)	993 (9.7%)
	Madagascar	0 (0%)	976 (11%)	980 (10%)	980 (9.5%)
	Malawi	936 (13%)	992 (11%)	1,000 (10%)	1,000 (9.7%)
	Mozambique	0 (0%)	896 (9.6%)	960 (9.8%)	990 (9.6%)
	Rwanda	992 (14%)	1,000 (11%)	1,000 (10%)	1,000 (9.7%)
	South Sudan	784 (11%)	616 (6.6%)	0 (0%)	0 (0%)
	Tanzania	968 (14%)	960 (10%)	970 (9.9%)	1,000 (9.7%)
	Uganda	656 (9.4%)	960 (10%)	1,000 (10%)	1,000 (9.7%)
	Zimbabwe	936 (13%)	944 (10%)	980 (10%)	1,082 (11%)
Middle Africa	country				
	Cameroon	944 (24%)	1,000 (17%)	990 (26%)	980 (23%)
	Central African Republic	0 (0%)	1,000 (17%)	0 (0%)	0 (0%)
	Chad	1,000 (26%)	1,000 (17%)	990 (26%)	1,111 (27%)
	Congo (Kinshasa)	0 (0%)	1,000 (17%)	0 (0%)	0 (0%)
	Congo Brazzaville	1,000 (26%)	984 (17%)	1,000 (26%)	1,090 (26%)

(continued)

Group	Country	2016	2017	2018	2019
	Gabon	912 (24%)	888 (15%)	860 (22%)	990 (24%)
Southern Africa	country				
	Lesotho	840 (100%)	900 (51%)	0 (0%)	970 (52%)
	Namibia	0 (0%)	864 (49%)	878 (100%)	892 (48%)
Western Africa	country				
	Benin	704 (19%)	1,000 (8.4%)	980 (8.7%)	1,000 (7.1%)
	Burkina Faso	24 (0.6%)	1,000 (8.4%)	1,000 (8.8%)	1,000 (7.1%)
	Ghana	264 (7.0%)	464 (3.9%)	770 (6.8%)	969 (6.9%)
	Guinea	0 (0%)	984 (8.3%)	1,000 (8.8%)	1,130 (8.1%)
	Ivory Coast	0 (0%)	976 (8.2%)	930 (8.2%)	0 (0%)
	Liberia	0 (0%)	848 (7.2%)	530 (4.7%)	930 (6.6%)
	Mali	0 (0%)	896 (7.6%)	890 (7.9%)	1,010 (7.2%)
	Mauritania	0 (0%)	1,000 (8.4%)	930 (8.2%)	1,100 (7.8%)
	Niger	976 (26%)	960 (8.1%)	720 (6.4%)	760 (5.4%)
	Nigeria	808 (21%)	808 (6.8%)	890 (7.9%)	2,960 (21%)
	Senegal	0 (0%)	992 (8.4%)	980 (8.7%)	990 (7.1%)
	Sierra Leone	0 (0%)	912 (7.7%)	680 (6.0%)	1,042 (7.4%)
	Togo	1,000 (26%)	1,000 (8.4%)	1,000 (8.8%)	1,130 (8.1%)

11.3 Pooled Summary Statistics

Table 6: Summary statistics for pooled data.

Group	Variable	2016 (N=15424)	2017 (N=28764)	2018 (N=25780)	2019 (N=30321)
GWP	SWB (0-10)	4.0 (2.0, 5.0)	4.0 (2.0, 6.0)	5.0 (3.0, 6.0)	5.0 (2.0, 6.0)
	Unknown	225	1,045	1,246	766
	Gender				
	Male	7,226 (47%)	14,277 (50%)	13,595 (53%)	15,203 (50%)
	Female	8,198 (53%)	14,487 (50%)	12,185 (47%)	15,118 (50%)
	Age	30 (22, 41)	30 (22, 42)	30 (23, 41)	30 (22, 40)
	Income	505 (187, 1,220)	632 (230, 1,642)	666 (252, 1,678)	608 (236, 1,456)
	Unknown	0	1,000	1,650	1,082
	Urbanicity				
	Rural Area	5,887 (41%)	10,273 (36%)	9,578 (37%)	9,885 (33%)
	Small Town	5,274 (36%)	11,059 (38%)	8,787 (34%)	12,630 (42%)
	Large City	2,302 (16%)	5,066 (18%)	4,279 (17%)	5,167 (17%)
	Suburb	1,017 (7.0%)	2,366 (8.2%)	3,136 (12%)	2,639 (8.7%)
	Unknown	944	0	0	0
30 days	FC Before	9 (9, 13)	7 (0, 54)	16 (0, 65)	8 (1, 41)
	Unknown	15,383	6,090	5,667	5,267
	FC After	27 (19, 28)	11 (0, 64)	15 (0, 59)	8 (1, 39)
	Unknown	15,383	6,090	5,667	5,267
	FCC	7 (4, 8)	3 (0, 18)	6 (0, 21)	4 (0, 15)
	Unknown	15,383	6,090	5,667	5,267
	FCC (%)	60 (40, 74)	53 (22, 94)	49 (24, 87)	62 (31, 95)
	Unknown	15,383	9,393	8,375	7,530
	Mean FAD Before	515 (418, 521)	739 (231, 1,187)	470 (177, 1,117)	805 (314, 1,205)

(continued)

Group	Variable	2016 (N=15424)	2017 (N=28764)	2018 (N=25780)	2019 (N=30321)
	Unknown	15,383	8,942	8,001	6,922
	Mean FAD After	379 (289, 421)	637 (175, 1,168)	494 (169, 1,106)	774 (350, 1,181)
	Unknown	15,383	9,103	8,253	7,222
	FADC	-0.10 (-0.13, 0.01)	0.00 (-0.23, 0.19)	0.01 (-0.14, 0.17)	0.00 (-0.19, 0.18)
	Unknown	15,383	10,627	9,412	8,650
	FADC (%)	-26 (-33, 2)	1 (-42, 44)	3 (-32, 46)	-1 (-29, 34)
	Unknown	15,383	10,627	9,412	8,650
90 days	FC Before	25 (10, 44)	25 (2, 94)	23 (1, 79)	20 (2, 74)
	Unknown	15,047	823	932	1,834
	FC After	99 (54, 175)	26 (2, 101)	31 (2, 89)	21 (3, 75)
	Unknown	15,047	823	932	1,834
	FCC	5 (3, 11)	7 (1, 23)	5 (0, 17)	7 (1, 20)
	Unknown	15,047	823	932	1,834
	FCC (%)	27 (17, 33)	36 (15, 71)	30 (14, 58)	35 (17, 71)
	Unknown	15,071	2,742	3,798	3,307
	Mean FAD Before	515 (310, 772)	480 (133, 1,006)	421 (137, 1,122)	535 (173, 1,064)
	Unknown	15,063	2,444	3,386	2,931
	Mean FAD After	90 (49, 193)	442 (127, 1,020)	335 (118, 1,012)	495 (177, 989)
	Unknown	15,047	2,682	2,823	3,433
	FADC	-0.34 (-0.67, -0.17)	0.00 (-0.12, 0.14)	-0.01 (-0.17, 0.04)	0.00 (-0.12, 0.11)
	Unknown	15,063	3,080	3,808	4,062
	FADC (%)	-76 (-89, -56)	1 (-31, 50)	-5 (-34, 17)	0 (-24, 33)
	Unknown	15,063	3,080	3,808	4,062

(continued)

Group	Variable	2016 (N=15424)	2017 (N=28764)	2018 (N=25780)	2019 (N=30321)
180 days	FC Before	25 (10, 44)	41 (5, 138)	35 (3, 102)	29 (3, 100)
	Unknown	15,047	224	110	10
	FC After	71 (42, 136)	36 (6, 130)	40 (4, 107)	27 (2, 99)
	Unknown	15,047	224	110	10
	FCC	6 (3, 11)	7 (1, 21)	6 (1, 16)	6 (1, 16)
	Unknown	15,047	224	110	10
	FCC (%)	28 (22, 42)	23 (9, 47)	21 (9, 42)	24 (11, 49)
	Unknown	15,071	1,273	2,239	2,001
	Mean FAD Before	515 (310, 772)	322 (79, 861)	335 (101, 893)	397 (114, 923)
	Unknown	15,063	1,137	1,998	1,723
	Mean FAD After	101 (72, 216)	341 (85, 794)	288 (94, 835)	422 (119, 973)
	Unknown	15,047	1,277	1,766	1,924
	FADC	-0.33 (-0.67, -0.17)	0.00 (-0.07, 0.09)	0.00 (-0.08, 0.04)	0.00 (-0.06, 0.07)
	Unknown	15,063	1,550	2,197	2,298
	FADC (%)	-75 (-88, -48)	0 (-21, 40)	-4 (-26, 19)	1 (-16, 24)
	Unknown	15,063	1,550	2,197	2,298

[1] Median (IQR); n (%)

11.4 Graphical Analysis of the FAD(C)-FC(C) Relationship

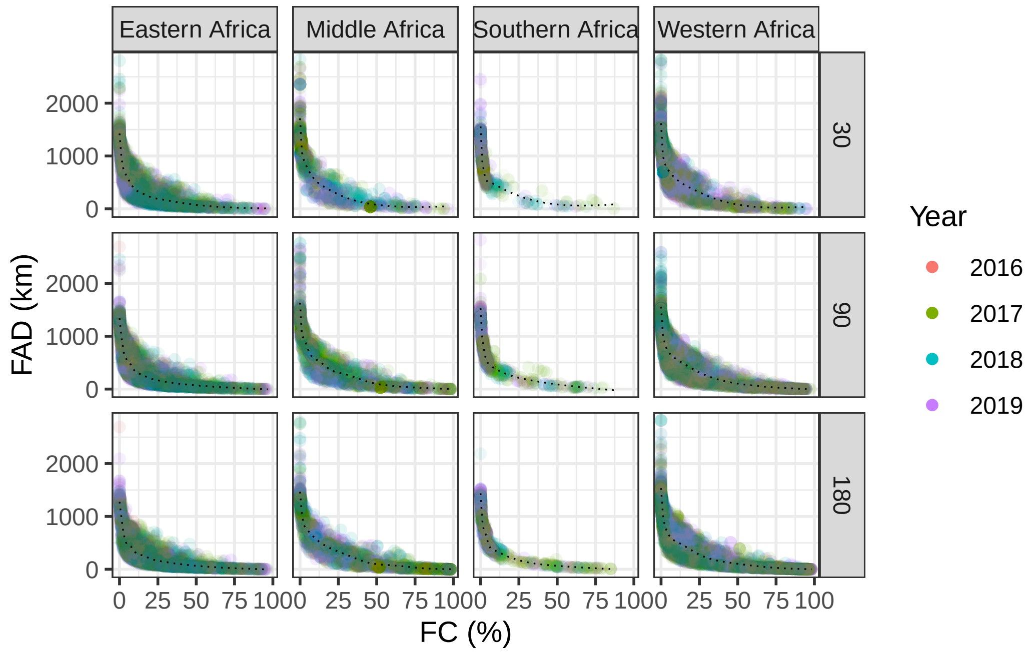

Figure 12: Scatterplot of Forest Attrition Distance and Forest Cover at the beginning of the recall period (for 30, 90 and 180 days recall).

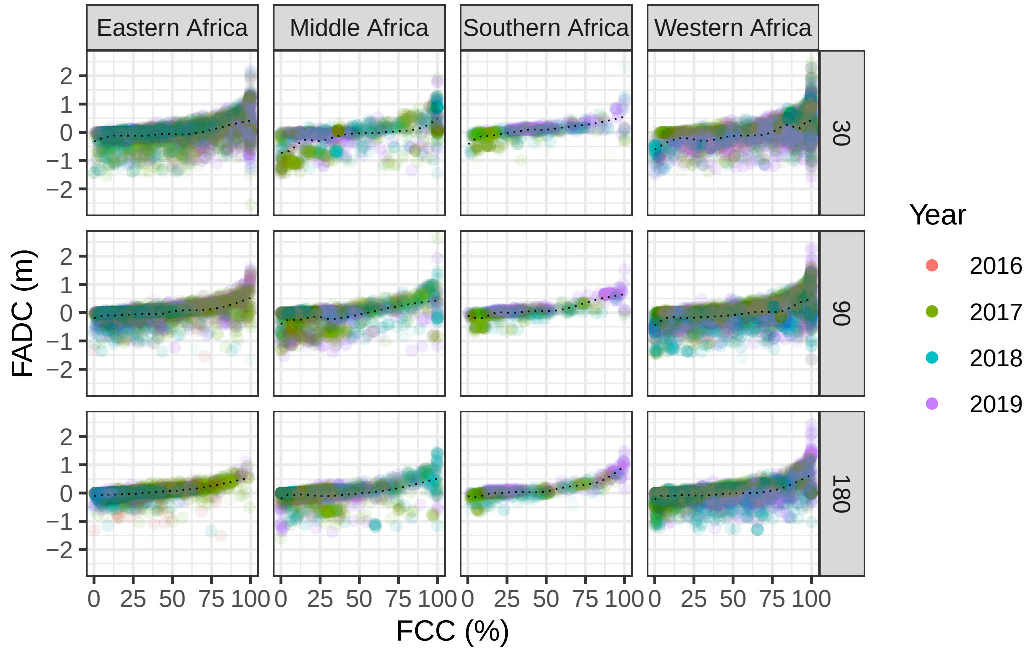

Figure 13: Scatterplot of Forest Attrition Distance change and Forest Cover Loss during the recall period (for 30, 90 and 180 days recall).

11.5 Summary Statistics by Region

Table 7: Summary Statistics for Eastern Africa.

Group	Variable	2016 (N=6952)	2017 (N=9288)	2018 (N=9762)	2019 (N=10267)
GWP	SWB (0-10)	4.0 (2.0, 5.0)	4.0 (2.0, 5.0)	4.0 (2.0, 5.0)	4.0 (2.0, 5.0)
	Unknown	63	231	254	210
	Gender				
	Male	2,904 (42%)	3,891 (42%)	4,357 (45%)	4,520 (44%)
	Female	4,048 (58%)	5,397 (58%)	5,405 (55%)	5,747 (56%)
	Age	30 (22, 41)	30 (23, 42)	30 (23, 42)	30 (23, 41)
	Income	385 (134, 961)	548 (192, 1,414)	490 (186, 1,248)	458 (163, 1,090)

(continued)

Group	Variable	2016 (N=6952)	2017 (N=9288)	2018 (N=9762)	2019 (N=10267)
	Unknown	0	0	0	1,082
	Urbanicity				
	Rural Area	3,790 (55%)	5,077 (55%)	5,780 (59%)	5,754 (56%)
	Small Town	2,126 (31%)	2,747 (30%)	2,220 (23%)	2,949 (29%)
	Large City	457 (6.6%)	577 (6.2%)	632 (6.5%)	740 (7.2%)
	Suburb	579 (8.3%)	887 (9.5%)	1,130 (12%)	824 (8.0%)
30 days	FC Before	9 (9, 13)	33 (9, 79)	47 (22, 86)	21 (5, 64)
	Unknown	6,911	839	562	587
	FC After	27 (19, 28)	37 (8, 88)	47 (20, 94)	19 (3, 59)
	Unknown	6,911	839	562	587
	FCC	7 (4, 8)	11 (4, 27)	14 (6, 25)	8 (3, 19)
	Unknown	6,911	839	562	587
	FCC (%)	60 (40, 74)	49 (25, 80)	36 (18, 59)	51 (24, 90)
	Unknown	6,911	1,046	726	722
	Mean FAD Before	515 (418, 521)	413 (163, 834)	229 (115, 490)	432 (202, 909)
	Unknown	6,911	989	678	674
	Mean FAD After	379 (289, 421)	350 (131, 797)	231 (97, 479)	477 (211, 973)
	Unknown	6,911	1,119	650	923
	FADC	-0.10 (-0.13, 0.01)	-0.02 (-0.23, 0.15)	0.00 (-0.09, 0.08)	0.00 (-0.10, 0.18)
	Unknown	6,911	1,267	786	1,055
	FADC (%)	-26 (-33, 2)	-7 (-51, 43)	3 (-29, 36)	1 (-25, 44)
	Unknown	6,911	1,267	786	1,055
90 days	FC Before	25 (10, 44)	48 (19, 104)	61 (28, 108)	39 (14, 85)

(continued)

Group	Variable	2016 (N=6952)	2017 (N=9288)	2018 (N=9762)	2019 (N=10267)
	Unknown	6,575	48	24	32
	FC After	99 (54, 175)	44 (14, 100)	68 (36, 117)	36 (13, 81)
	Unknown	6,575	48	24	32
	FCC	5 (3, 11)	14 (6, 32)	12 (5, 21)	10 (4, 22)
	Unknown	6,575	48	24	32
	FCC (%)	27 (17, 33)	37 (20, 63)	22 (12, 36)	30 (16, 51)
	Unknown	6,599	90	54	116
	Mean FAD Before	515 (310, 772)	240 (108, 561)	182 (81, 379)	277 (120, 578)
	Unknown	6,591	74	44	53
	Mean FAD After	90 (49, 193)	248 (108, 632)	153 (74, 298)	310 (131, 597)
	Unknown	6,575	56	24	61
	FADC	-0.34 (-0.67, -0.17)	0.01 (-0.06, 0.10)	0.00 (-0.06, 0.02)	0.00 (-0.08, 0.08)
	Unknown	6,591	82	54	61
	FADC (%)	-76 (-89, -56)	3 (-25, 51)	-3 (-31, 16)	0 (-22, 40)
	Unknown	6,591	82	54	61
180 days	FC Before	25 (10, 44)	48 (21, 93)	63 (28, 112)	49 (22, 101)
	Unknown	6,575	0	0	0
	FC After	71 (42, 136)	36 (15, 83)	70 (32, 115)	50 (20, 107)
	Unknown	6,575	0	0	0
	FCC	6 (3, 11)	14 (7, 31)	10 (4, 19)	8 (3, 16)
	Unknown	6,575	0	0	0
	FCC (%)	28 (22, 42)	35 (19, 55)	18 (9, 29)	18 (10, 32)
	Unknown	6,599	0	10	71

(continued)

Group	Variable	2016 (N=6952)	2017 (N=9288)	2018 (N=9762)	2019 (N=10267)
	Mean FAD Before	515 (310, 772)	254 (112, 458)	179 (78, 356)	214 (89, 434)
	Unknown	6,591	0	10	32
	Mean FAD After	101 (72, 216)	303 (141, 557)	152 (75, 301)	220 (92, 433)
	Unknown	6,575	0	10	32
	FADC	-0.33 (-0.67, -0.17)	0.03 (-0.02, 0.14)	-0.01 (-0.06, 0.01)	0.00 (-0.04, 0.04)
	Unknown	6,591	0	10	32
	FADC (%)	-75 (-88, -48)	18 (-12, 68)	-6 (-27, 15)	-1 (-19, 22)
	Unknown	6,591	0	10	32

[1] Median (IQR); n (%)

Table 8: Summary Statistics for Middle Africa.

Group	Variable	2016 (N=3856)	2017 (N=5872)	2018 (N=3840)	2019 (N=4171)
GWP	SWB (0-10)	5.0 (3.0, 6.0)	5.0 (3.0, 6.0)	5.0 (3.0, 7.0)	5.0 (3.0, 7.0)
	Unknown	60	235	275	106
	Gender				
	Male	1,956 (51%)	3,166 (54%)	2,250 (59%)	2,318 (56%)
	Female	1,900 (49%)	2,706 (46%)	1,590 (41%)	1,853 (44%)
	Age	30 (22, 41)	30 (23, 42)	30 (22, 41)	30 (22, 40)
	Income	812 (307, 1,933)	740 (249, 2,046)	876 (337, 2,021)	818 (344, 1,873)
	Urbanicity				
	Rural Area	288 (9.9%)	1,211 (21%)	770 (20%)	549 (13%)
	Small Town	1,240 (43%)	2,351 (40%)	1,420 (37%)	1,738 (42%)

(continued)

Group	Variable	2016 (N=3856)	2017 (N=5872)	2018 (N=3840)	2019 (N=4171)
	Large City	1,232 (42%)	1,992 (34%)	1,480 (39%)	1,703 (41%)
	Suburb	152 (5.2%)	318 (5.4%)	170 (4.4%)	181 (4.3%)
	Unknown	944	0	0	0
30 days	FC Before	NA (NA, NA)	3 (0, 61)	18 (0, 94)	6 (0, 59)
	Unknown	3,856	1,907	1,164	1,181
	FC After	NA (NA, NA)	31 (1, 105)	22 (1, 78)	21 (3, 75)
	Unknown	3,856	1,907	1,164	1,181
	FCC	NA (NA, NA)	1 (0, 19)	7 (0, 41)	3 (0, 18)
	Unknown	3,856	1,907	1,164	1,181
	FCC (%)	NA (NA, NA)	37 (12, 86)	52 (28, 96)	35 (19, 90)
	Unknown	3,856	2,440	1,544	1,719
	Mean FAD Before	NA (NA, NA)	1,102 (254, 1,295)	570 (200, 1,058)	805 (223, 1,242)
	Unknown	3,856	2,232	1,463	1,539
	Mean FAD After	NA (NA, NA)	486 (97, 1,207)	599 (220, 1,005)	599 (156, 882)
	Unknown	3,856	2,223	1,378	1,428
	FADC	NA (NA, NA)	0.00 (-0.82, 0.06)	0.00 (-0.30, 0.25)	-0.06 (-0.32, 0.01)
	Unknown	3,856	2,570	1,581	1,795
	FADC (%)	NA (NA, NA)	1 (-77, 70)	0 (-54, 74)	-22 (-44, 3)
	Unknown	3,856	2,570	1,581	1,795
90 days	FC Before	NA (NA, NA)	46 (3, 161)	40 (4, 102)	27 (2, 101)
	Unknown	3,856	503	230	92
	FC After	NA (NA, NA)	99 (11, 148)	40 (8, 92)	62 (18, 124)
	Unknown	3,856	503	230	92

(continued)

Group	Variable	2016 (N=3856)	2017 (N=5872)	2018 (N=3840)	2019 (N=4171)
	FCC	NA (NA, NA)	6 (1, 28)	7 (2, 18)	7 (0, 19)
	Unknown	3,856	503	230	92
	FCC (%)	NA (NA, NA)	22 (9, 42)	32 (12, 68)	27 (13, 43)
	Unknown	3,856	884	540	523
	Mean FAD Before	NA (NA, NA)	506 (68, 1,065)	440 (178, 910)	515 (149, 1,123)
	Unknown	3,856	747	410	342
	Mean FAD After	NA (NA, NA)	286 (64, 783)	436 (186, 908)	415 (129, 734)
	Unknown	3,856	648	350	142
	FADC	NA (NA, NA)	-0.03 (-0.53, 0.05)	0.00 (-0.11, 0.09)	-0.02 (-0.30, 0.03)
	Unknown	3,856	776	510	381
	FADC (%)	NA (NA, NA)	-15 (-68, 77)	-1 (-27, 32)	-11 (-52, 13)
	Unknown	3,856	776	510	381
180 days	FC Before	NA (NA, NA)	127 (12, 207)	59 (6, 130)	59 (16, 132)
	Unknown	3,856	224	0	0
	FC After	NA (NA, NA)	126 (33, 200)	52 (8, 119)	65 (18, 142)
	Unknown	3,856	224	0	0
	FCC	NA (NA, NA)	10 (2, 24)	8 (1, 15)	8 (3, 20)
	Unknown	3,856	224	0	0
	FCC (%)	NA (NA, NA)	14 (7, 32)	28 (8, 71)	20 (9, 38)
	Unknown	3,856	331	280	106
	Mean FAD Before	NA (NA, NA)	118 (38, 800)	413 (108, 825)	420 (112, 803)
	Unknown	3,856	299	180	50
	Mean FAD After	NA (NA, NA)	206 (45, 542)	473 (122, 833)	426 (92, 725)

(continued)

Group	Variable	2016 (N=3856)	2017 (N=5872)	2018 (N=3840)	2019 (N=4171)
	Unknown	3,856	272	156	30
	FADC	NA (NA, NA)	0.00 (-0.12, 0.02)	0.02 (-0.03, 0.15)	0.00 (-0.10, 0.05)
	Unknown	3,856	307	216	60
	FADC (%)	NA (NA, NA)	2 (-29, 53)	7 (-21, 36)	0 (-17, 24)
	Unknown	3,856	307	216	60

[1] Median (IQR); n (%)

Table 9: Summary Statistics for Southern Africa.

Group	Variable	2016 (N=840)	2017 (N=1764)	2018 (N=878)	2019 (N=1862)
GWP	SWB (0-10)	4.0 (1.0, 5.0)	4.0 (2.0, 6.0)	5.0 (4.0, 6.0)	4.0 (2.0, 6.0)
	Unknown	10	47	9	35
	Gender				
	Male	326 (39%)	653 (37%)	364 (41%)	774 (42%)
	Female	514 (61%)	1,111 (63%)	514 (59%)	1,088 (58%)
	Age	37 (24, 59)	30 (23, 45)	29 (23, 36)	30 (23, 45)
	Income	483 (167, 1,393)	1,321 (467, 3,576)	2,878 (1,228, 7,369)	932 (410, 2,500)
	Urbanicity				
	Rural Area	600 (71%)	834 (47%)	97 (11%)	675 (36%)
	Small Town	216 (26%)	675 (38%)	390 (44%)	919 (49%)
	Large City	24 (2.9%)	143 (8.1%)	24 (2.7%)	103 (5.5%)
	Suburb	0 (0%)	112 (6.3%)	367 (42%)	165 (8.9%)
30 days	FC Before	NA (NA, NA)	6 (3, 10)	2 (0, 31)	2 (0, 6)
	Unknown	840	342	0	0

(continued)

Group	Variable	2016 (N=840)	2017 (N=1764)	2018 (N=878)	2019 (N=1862)
	FC After	NA (NA, NA)	9 (4, 31)	2 (0, 14)	1 (0, 3)
	Unknown	840	342	0	0
	FCC	NA (NA, NA)	1 (0, 1)	1 (0, 14)	1 (0, 3)
	Unknown	840	342	0	0
	FCC (%)	NA (NA, NA)	14 (9, 25)	48 (27, 68)	46 (37, 73)
	Unknown	840	390	50	267
	Mean FAD Before	NA (NA, NA)	750 (576, 935)	899 (442, 1,352)	998 (720, 1,303)
	Unknown	840	390	36	202
	Mean FAD After	NA (NA, NA)	648 (357, 922)	971 (576, 1,293)	1,137 (870, 1,333)
	Unknown	840	354	28	313
	FADC	NA (NA, NA)	-0.06 (-0.15, -0.01)	0.08 (-0.03, 0.17)	0.14 (0.10, 0.21)
	Unknown	840	397	36	337
	FADC (%)	NA (NA, NA)	-9 (-22, -1)	8 (-8, 31)	17 (10, 27)
	Unknown	840	397	36	337
90 days	FC Before	NA (NA, NA)	9 (5, 35)	9 (1, 48)	4 (0, 10)
	Unknown	840	0	0	0
	FC After	NA (NA, NA)	17 (8, 41)	7 (1, 33)	1 (0, 7)
	Unknown	840	0	0	0
	FCC	NA (NA, NA)	1 (0, 13)	4 (0, 14)	1 (0, 3)
	Unknown	840	0	0	0
	FCC (%)	NA (NA, NA)	11 (6, 35)	38 (19, 53)	35 (22, 88)
	Unknown	840	44	16	85
	Mean FAD Before	NA (NA, NA)	627 (352, 878)	673 (316, 1,253)	870 (590, 1,277)

(continued)

Group	Variable	2016 (N=840)	2017 (N=1764)	2018 (N=878)	2019 (N=1862)
	Unknown	840	24	16	72
	Mean FAD After	NA (NA, NA)	490 (294, 798)	684 (320, 1,217)	1,039 (779, 1,327)
	Unknown	840	18	3	192
	FADC	NA (NA, NA)	-0.08 (-0.13, 0.02)	0.00 (-0.04, 0.08)	0.09 (0.04, 0.45)
	Unknown	840	34	24	192
	FADC (%)	NA (NA, NA)	-13 (-21, 8)	0 (-11, 12)	12 (5, 48)
	Unknown	840	34	24	192
180 days	FC Before	NA (NA, NA)	16 (5, 93)	8 (1, 41)	8 (1, 19)
	Unknown	840	0	0	0
	FC After	NA (NA, NA)	19 (9, 41)	7 (1, 25)	2 (0, 12)
	Unknown	840	0	0	0
	FCC	NA (NA, NA)	2 (1, 22)	3 (0, 13)	2 (0, 6)
	Unknown	840	0	0	0
	FCC (%)	NA (NA, NA)	18 (7, 51)	31 (14, 48)	32 (19, 92)
	Unknown	840	24	12	10
	Mean FAD Before	NA (NA, NA)	449 (133, 843)	649 (353, 1,195)	715 (417, 1,196)
	Unknown	840	24	6	10
	Mean FAD After	NA (NA, NA)	462 (289, 739)	632 (354, 1,132)	1,006 (586, 1,287)
	Unknown	840	24	0	111
	FADC	NA (NA, NA)	0.00 (-0.06, 0.09)	-0.01 (-0.13, 0.09)	0.10 (0.05, 0.50)
	Unknown	840	24	6	111
	FADC (%)	NA (NA, NA)	-3 (-10, 35)	-4 (-26, 12)	15 (7, 92)

(continued)

Group	Variable	2016 (N=840)	2017 (N=1764)	2018 (N=878)	2019 (N=1862)
	Unknown	840	24	6	111

[1] Median (IQR); n (%)

Table 10: Summary Statistics for Western Africa.

Group	Variable	2016 (N=3776)	2017 (N=11840)	2018 (N=11300)	2019 (N=14021)
GWP	SWB (0-10)	4.0 (3.0, 6.0)	5.0 (3.0, 6.0)	5.0 (3.0, 6.0)	5.0 (3.0, 6.0)
	Unknown	92	532	708	415
	Gender				
	Male	2,040 (54%)	6,567 (55%)	6,624 (59%)	7,591 (54%)
	Female	1,736 (46%)	5,273 (45%)	4,676 (41%)	6,430 (46%)
	Age	29 (22, 40)	30 (22, 41)	30 (22, 40)	30 (22, 40)
	Income	508 (217, 1,114)	601 (243, 1,457)	728 (294, 1,645)	621 (255, 1,477)
	Unknown	0	1,000	1,650	0
	Urbanicity				
	Rural Area	1,209 (32%)	3,151 (27%)	2,931 (26%)	2,907 (21%)
	Small Town	1,692 (45%)	5,286 (45%)	4,757 (42%)	7,024 (50%)
	Large City	589 (16%)	2,354 (20%)	2,143 (19%)	2,621 (19%)
	Suburb	286 (7.6%)	1,049 (8.9%)	1,469 (13%)	1,469 (10%)
30 days	FC Before	NA (NA, NA)	1 (0, 15)	0 (0, 4)	2 (0, 21)
	Unknown	3,776	3,002	3,941	3,499
	FC After	NA (NA, NA)	0 (0, 13)	0 (0, 4)	3 (0, 19)
	Unknown	3,776	3,002	3,941	3,499
	FCC	NA (NA, NA)	1 (0, 10)	0 (0, 4)	1 (0, 12)

(continued)

Group	Variable	2016 (N=3776)	2017 (N=11840)	2018 (N=11300)	2019 (N=14021)
	Unknown	3,776	3,002	3,941	3,499
	FCC (%)	NA (NA, NA)	88 (42, 100)	90 (52, 100)	82 (46, 99)
	Unknown	3,776	5,517	6,055	4,822
	Mean FAD Before	NA (NA, NA)	1,065 (471, 1,308)	1,182 (700, 1,362)	1,050 (595, 1,328)
	Unknown	3,776	5,331	5,824	4,507
	Mean FAD After	NA (NA, NA)	1,117 (586, 1,433)	1,185 (910, 1,372)	993 (608, 1,297)
	Unknown	3,776	5,407	6,197	4,558
	FADC	NA (NA, NA)	0.09 (-0.03, 0.41)	0.04 (-0.34, 0.49)	-0.05 (-0.33, 0.22)
	Unknown	3,776	6,393	7,009	5,463
	FADC (%)	NA (NA, NA)	11 (-18, 57)	4 (-30, 68)	-6 (-32, 35)
	Unknown	3,776	6,393	7,009	5,463
90 days	FC Before	NA (NA, NA)	6 (0, 59)	1 (0, 15)	9 (1, 61)
	Unknown	3,776	272	678	1,710
	FC After	NA (NA, NA)	3 (0, 48)	2 (0, 31)	6 (0, 58)
	Unknown	3,776	272	678	1,710
	FCC	NA (NA, NA)	2 (0, 14)	0 (0, 6)	4 (0, 20)
	Unknown	3,776	272	678	1,710
	FCC (%)	NA (NA, NA)	58 (25, 88)	55 (20, 87)	57 (20, 91)
	Unknown	3,776	1,724	3,188	2,583
	Mean FAD Before	NA (NA, NA)	820 (233, 1,303)	1,128 (560, 1,355)	844 (292, 1,230)
	Unknown	3,776	1,599	2,916	2,464
	Mean FAD After	NA (NA, NA)	953 (265, 1,322)	999 (380, 1,306)	791 (305, 1,221)
	Unknown	3,776	1,960	2,446	3,038

(continued)

Group	Variable	2016 (N=3776)	2017 (N=11840)	2018 (N=11300)	2019 (N=14021)
	FADC	NA (NA, NA)	0.03 (-0.09, 0.24)	-0.09 (-0.39, 0.11)	0.00 (-0.18, 0.18)
	Unknown	3,776	2,188	3,220	3,428
	FADC (%)	NA (NA, NA)	8 (-20, 49)	-12 (-43, 16)	-2 (-26, 33)
	Unknown	3,776	2,188	3,220	3,428
180 days	FC Before	NA (NA, NA)	10 (0, 128)	5 (0, 66)	11 (0, 94)
	Unknown	3,776	0	110	10
	FC After	NA (NA, NA)	14 (1, 125)	8 (0, 87)	9 (0, 77)
	Unknown	3,776	0	110	10
	FCC	NA (NA, NA)	2 (0, 8)	2 (0, 10)	4 (0, 15)
	Unknown	3,776	0	110	10
	FCC (%)	NA (NA, NA)	16 (6, 44)	25 (10, 58)	35 (12, 69)
	Unknown	3,776	918	1,937	1,814
	Mean FAD Before	NA (NA, NA)	644 (85, 1,215)	798 (182, 1,261)	698 (146, 1,227)
	Unknown	3,776	814	1,802	1,631
	Mean FAD After	NA (NA, NA)	571 (77, 1,163)	635 (144, 1,213)	721 (181, 1,268)
	Unknown	3,776	981	1,600	1,751
	FADC	NA (NA, NA)	0.00 (-0.10, 0.05)	-0.01 (-0.22, 0.05)	0.00 (-0.10, 0.09)
	Unknown	3,776	1,219	1,965	2,095
	FADC (%)	NA (NA, NA)	-7 (-27, 11)	-4 (-26, 18)	0 (-16, 23)
	Unknown	3,776	1,219	1,965	2,095

[1] Median (IQR); n (%)

11.6 Summary Statistics by Country

11.6.1 Eastern Africa (A-Z)

Table 11: Summary Statistics for Burundi.

Group	Variable	2018 (N=880)
GWP	SWB (0-10)	4.0 (1.0, 5.0)
	Unknown	84
	Gender	
	Male	388 (44%)
	Female	492 (56%)
	Age	30 (23, 42)
	Income	172 (34, 515)
	Urbanicity	
	Rural Area	720 (82%)
	Small Town	80 (9.1%)
	Large City	20 (2.3%)
	Suburb	60 (6.8%)
30 days	FC Before	41 (33, 59)
	FC After	23 (13, 42)
	FCC	26 (13, 41)
	FCC (%)	68 (37, 85)
	Mean FAD Before	212 (159, 373)
	Mean FAD After	466 (255, 712)
	FADC	0.15 (-0.01, 0.48)
	FADC (%)	71 (-8, 225)

(continued)

Group	Variable	2018 (N=880)
90 days	FC Before	93 (73, 107)
	FC After	59 (46, 91)
	FCC	32 (21, 42)
	FCC (%)	37 (22, 49)
	Mean FAD Before	79 (60, 106)
	Mean FAD After	129 (74, 154)
	FADC	0.03 (0.01, 0.05)
	FADC (%)	42 (3, 65)
180 days	FC Before	97 (75, 116)
	FC After	74 (63, 111)
	FCC	22 (17, 31)
	FCC (%)	24 (16, 37)
	Mean FAD Before	75 (53, 100)
	Mean FAD After	97 (57, 119)
	FADC	0.01 (-0.01, 0.03)
	FADC (%)	12 (-4, 33)

[1] Median (IQR); n (%)

Table 12: Summary Statistics for Ethiopia.

Group	Variable	2016 (N=840)	2017 (N=1000)	2018 (N=1000)	2019 (N=2222)
GWP	SWB (0-10)	5.00 (3.00, 5.00)	4.00 (3.00, 5.00)	5.00 (3.00, 5.00)	5.00 (2.00, 5.00)
	Unknown	14	7	3	54

(continued)

Group	Variable	2016 (N=840)	2017 (N=1000)	2018 (N=1000)	2019 (N=2222)
	Gender				
	Male	350 (42%)	398 (40%)	430 (43%)	976 (44%)
	Female	490 (58%)	602 (60%)	570 (57%)	1,246 (56%)
	Age	28 (20, 38)	30 (23, 40)	30 (22, 40)	29 (23, 38)
	Income	489 (181, 978)	731 (366, 1,462)	676 (406, 1,353)	770 (407, 1,527)
	Urbanicity				
	Rural Area	483 (58%)	396 (40%)	626 (63%)	1,366 (61%)
	Small Town	231 (28%)	419 (42%)	135 (14%)	537 (24%)
	Large City	120 (14%)	167 (17%)	226 (23%)	293 (13%)
	Suburb	6 (0.7%)	18 (1.8%)	13 (1.3%)	26 (1.2%)
30 days	FC Before	NA (NA, NA)	2 (0, 6)	4 (1, 12)	4 (1, 19)
	Unknown	840	88	80	223
	FC After	NA (NA, NA)	4 (1, 13)	3 (0, 10)	2 (0, 12)
	Unknown	840	88	80	223
	FCC	NA (NA, NA)	1 (0, 4)	2 (1, 7)	2 (1, 15)
	Unknown	840	88	80	223
	FCC (%)	NA (NA, NA)	74 (45, 96)	77 (54, 96)	94 (71, 100)
	Unknown	840	136	160	326
	Mean FAD Before	NA (NA, NA)	1,129 (881, 1,328)	955 (660, 1,236)	980 (639, 1,227)
	Unknown	840	120	130	294
	Mean FAD After	NA (NA, NA)	969 (640, 1,218)	1,030 (757, 1,253)	1,058 (745, 1,263)
	Unknown	840	96	152	430
	FADC	NA (NA, NA)	-0.16 (-0.46, 0.09)	0.06 (-0.16, 0.32)	0.04 (-0.20, 0.33)

(continued)

Group	Variable	2016 (N=840)	2017 (N=1000)	2018 (N=1000)	2019 (N=2222)
	Unknown	840	128	212	500
	FADC (%)	NA (NA, NA)	-14 (-42, 7)	8 (-18, 36)	5 (-22, 48)
	Unknown	840	128	212	500
90 days	FC Before	NA (NA, NA)	4 (1, 21)	8 (2, 28)	8 (2, 28)
	Unknown	840	0	0	0
	FC After	NA (NA, NA)	8 (2, 26)	10 (1, 31)	9 (3, 31)
	Unknown	840	0	0	0
	FCC	NA (NA, NA)	2 (0, 6)	3 (1, 6)	2 (1, 11)
	Unknown	840	0	0	0
	FCC (%)	NA (NA, NA)	27 (16, 55)	35 (18, 57)	41 (18, 75)
	Unknown	840	16	10	84
	Mean FAD Before	NA (NA, NA)	880 (540, 1,153)	711 (413, 1,062)	855 (528, 1,095)
	Unknown	840	8	10	21
	Mean FAD After	NA (NA, NA)	705 (384, 1,058)	748 (419, 1,175)	742 (487, 1,023)
	Unknown	840	0	0	21
	FADC	NA (NA, NA)	-0.09 (-0.24, 0.02)	0.01 (-0.05, 0.13)	-0.14 (-0.31, 0.12)
	Unknown	840	8	10	21
	FADC (%)	NA (NA, NA)	-10 (-29, 4)	3 (-10, 15)	-17 (-37, 24)
	Unknown	840	8	10	21
180 days	FC Before	NA (NA, NA)	14 (4, 50)	13 (3, 53)	11 (2, 34)
	Unknown	840	0	0	0
	FC After	NA (NA, NA)	15 (5, 42)	18 (3, 61)	10 (3, 31)
	Unknown	840	0	0	0

(continued)

Group	Variable	2016 (N=840)	2017 (N=1000)	2018 (N=1000)	2019 (N=2222)
	FCC	NA (NA, NA)	3 (1, 15)	1 (0, 3)	2 (0, 6)
	Unknown	840	0	0	0
	FCC (%)	NA (NA, NA)	23 (15, 36)	10 (4, 18)	18 (7, 35)
	Unknown	840	0	10	63
	Mean FAD Before	NA (NA, NA)	516 (201, 919)	535 (241, 965)	738 (312, 1,051)
	Unknown	840	0	10	32
	Mean FAD After	NA (NA, NA)	497 (248, 867)	511 (180, 950)	755 (335, 1,021)
	Unknown	840	0	10	32
	FADC	NA (NA, NA)	0.01 (-0.08, 0.07)	-0.04 (-0.09, 0.00)	-0.02 (-0.12, 0.04)
	Unknown	840	0	10	32
	FADC (%)	NA (NA, NA)	3 (-12, 23)	-10 (-21, -1)	-5 (-17, 9)
	Unknown	840	0	10	32

[1] Median (IQR); n (%)

Table 13: Summary Statistics for Kenya.

Group	Variable	2016 (N=840)	2017 (N=944)	2018 (N=992)	2019 (N=993)
GWP	SWB (0-10)	5.0 (3.0, 6.0)	5.0 (3.0, 6.0)	5.0 (3.0, 6.0)	5.0 (2.5, 6.0)
	Unknown	4	6	10	14
	Gender				
	Male	377 (45%)	450 (48%)	496 (50%)	496 (50%)
	Female	463 (55%)	494 (52%)	496 (50%)	497 (50%)
	Age	28 (22, 39)	27 (22, 36)	28 (22, 38)	28 (23, 37)
	Income	577 (240, 1,442)	1,248 (535, 2,675)	1,123 (499, 2,496)	567 (227, 1,512)

(continued)

Group	Variable	2016 (N=840)	2017 (N=944)	2018 (N=992)	2019 (N=993)
	Urbanicity				
	Rural Area	501 (60%)	612 (65%)	598 (60%)	608 (61%)
	Small Town	269 (32%)	208 (22%)	202 (20%)	221 (22%)
	Large City	28 (3.3%)	17 (1.8%)	8 (0.8%)	40 (4.0%)
	Suburb	42 (5.0%)	107 (11%)	184 (19%)	124 (12%)
30 days	FC Before	NA (NA, NA)	22 (14, 53)	43 (5, 87)	39 (9, 86)
	Unknown	840	0	232	0
	FC After	NA (NA, NA)	11 (4, 24)	60 (19, 108)	44 (3, 105)
	Unknown	840	0	232	0
	FCC	NA (NA, NA)	13 (6, 29)	9 (2, 23)	14 (8, 28)
	Unknown	840	0	232	0
	FCC (%)	NA (NA, NA)	60 (42, 83)	32 (13, 60)	48 (24, 91)
	Unknown	840	36	256	8
	Mean FAD Before	NA (NA, NA)	391 (183, 759)	332 (106, 843)	398 (118, 808)
	Unknown	840	20	256	0
	Mean FAD After	NA (NA, NA)	687 (331, 917)	150 (69, 646)	370 (74, 1,065)
	Unknown	840	8	240	48
	FADC	NA (NA, NA)	0.14 (0.03, 0.35)	-0.05 (-0.28, 0.01)	-0.01 (-0.06, 0.30)
	Unknown	840	20	264	56
	FADC (%)	NA (NA, NA)	42 (10, 122)	-31 (-60, 6)	-3 (-45, 78)
	Unknown	840	20	264	56
90 days	FC Before	NA (NA, NA)	39 (22, 85)	16 (7, 36)	67 (46, 101)
	Unknown	840	0	0	0

(continued)

Group	Variable	2016 (N=840)	2017 (N=944)	2018 (N=992)	2019 (N=993)
	FC After	NA (NA, NA)	22 (11, 54)	50 (20, 94)	30 (13, 62)
	Unknown	840	0	0	0
	FCC	NA (NA, NA)	19 (9, 34)	2 (1, 4)	34 (22, 55)
	Unknown	840	0	0	0
	FCC (%)	NA (NA, NA)	46 (30, 65)	11 (6, 25)	59 (39, 78)
	Unknown	840	0	0	0
	Mean FAD Before	NA (NA, NA)	236 (108, 542)	523 (252, 848)	153 (76, 308)
	Unknown	840	0	0	0
	Mean FAD After	NA (NA, NA)	408 (180, 708)	223 (110, 438)	399 (133, 790)
	Unknown	840	0	0	0
	FADC	NA (NA, NA)	0.11 (0.03, 0.27)	-0.18 (-0.53, -0.08)	0.12 (0.05, 0.36)
	Unknown	840	0	0	0
	FADC (%)	NA (NA, NA)	49 (20, 114)	-49 (-64, -29)	77 (32, 205)
	Unknown	840	0	0	0
180 days	FC Before	NA (NA, NA)	38 (24, 87)	26 (12, 67)	34 (17, 66)
	Unknown	840	0	0	0
	FC After	NA (NA, NA)	23 (11, 51)	35 (18, 76)	27 (15, 51)
	Unknown	840	0	0	0
	FCC	NA (NA, NA)	20 (10, 34)	2 (1, 8)	8 (4, 15)
	Unknown	840	0	0	0
	FCC (%)	NA (NA, NA)	47 (31, 68)	10 (6, 17)	26 (17, 37)
	Unknown	840	0	0	8
	Mean FAD Before	NA (NA, NA)	233 (105, 531)	377 (155, 640)	276 (129, 498)

(continued)

Group	Variable	2016 (N=840)	2017 (N=944)	2018 (N=992)	2019 (N=993)
	Unknown	840	0	0	0
	Mean FAD After	NA (NA, NA)	445 (213, 675)	258 (135, 525)	337 (167, 564)
	Unknown	840	0	0	0
	FADC	NA (NA, NA)	0.11 (0.04, 0.26)	-0.07 (-0.13, -0.01)	0.03 (0.00, 0.07)
	Unknown	840	0	0	0
	FADC (%)	NA (NA, NA)	64 (29, 120)	-19 (-31, -3)	15 (0, 30)
	Unknown	840	0	0	0

[1] Median (IQR); n (%)

Table 14: Summary Statistics for Madagascar.

Group	Variable	2017 (N=976)	2018 (N=980)	2019 (N=980)
GWP	SWB (0-10)	4.00 (2.00, 5.00)	4.00 (2.00, 5.00)	4.00 (3.00, 5.00)
	Unknown	40	42	7
	Gender			
	Male	384 (39%)	452 (46%)	424 (43%)
	Female	592 (61%)	528 (54%)	556 (57%)
	Age	35 (24, 48)	34 (24, 46)	33 (23, 46)
	Income	345 (138, 828)	461 (194, 1,061)	299 (120, 718)
	Urbanicity			
	Rural Area	584 (60%)	620 (63%)	600 (61%)
	Small Town	144 (15%)	90 (9.2%)	192 (20%)
	Large City	176 (18%)	210 (21%)	130 (13%)
	Suburb	72 (7.4%)	60 (6.1%)	58 (5.9%)

(continued)

Group	Variable	2017 (N=976)	2018 (N=980)	2019 (N=980)
30 days	FC Before	46 (12, 100)	61 (31, 99)	76 (39, 163)
	Unknown	216	34	0
	FC After	4 (0, 56)	58 (25, 128)	62 (29, 136)
	Unknown	216	34	0
	FCC	25 (12, 55)	19 (10, 24)	11 (7, 36)
	Unknown	216	34	0
	FCC (%)	97 (44, 100)	32 (16, 59)	19 (9, 41)
	Unknown	232	44	0
	Mean FAD Before	437 (125, 790)	195 (92, 409)	137 (43, 252)
	Unknown	216	44	0
	Mean FAD After	588 (179, 1,170)	186 (76, 386)	207 (92, 367)
	Unknown	442	34	0
	FADC	0.15 (-0.07, 0.68)	0.01 (-0.04, 0.11)	0.00 (-0.02, 0.10)
	Unknown	444	44	0
	FADC (%)	32 (-26, 425)	11 (-28, 41)	3 (-14, 189)
	Unknown	444	44	0
90 days	FC Before	45 (18, 99)	77 (41, 135)	94 (53, 180)
	Unknown	8	0	0
	FC After	45 (16, 88)	88 (41, 179)	104 (57, 181)
	Unknown	8	0	0
	FCC	20 (11, 33)	16 (9, 20)	8 (5, 12)
	Unknown	8	0	0
	FCC (%)	51 (29, 84)	21 (9, 35)	10 (6, 17)

(continued)

Group	Variable	2017 (N=976)	2018 (N=980)	2019 (N=980)
	Unknown	18	0	0
	Mean FAD Before	377 (122, 763)	151 (86, 293)	95 (38, 204)
	Unknown	10	0	0
	Mean FAD After	248 (125, 618)	108 (47, 288)	87 (32, 184)
	Unknown	8	0	0
	FADC	-0.03 (-0.20, 0.09)	0.00 (-0.03, 0.03)	-0.01 (-0.03, 0.00)
	Unknown	10	0	0
	FADC (%)	-11 (-53, 56)	-1 (-45, 25)	-12 (-20, -4)
	Unknown	10	0	0
180 days	FC Before	43 (13, 82)	55 (27, 115)	88 (42, 176)
	FC After	28 (8, 74)	71 (34, 155)	98 (49, 168)
	FCC	16 (8, 28)	7 (4, 12)	7 (4, 13)
	FCC (%)	51 (35, 70)	14 (5, 25)	10 (7, 17)
	Mean FAD Before	355 (173, 515)	221 (83, 334)	105 (41, 233)
	Mean FAD After	340 (180, 623)	142 (60, 319)	92 (36, 205)
	FADC	0.10 (-0.08, 0.18)	-0.03 (-0.06, 0.00)	-0.01 (-0.04, 0.00)
	FADC (%)	34 (-23, 81)	-18 (-38, 0)	-12 (-23, 0)

[1] Median (IQR); n (%)

Table 15: Summary Statistics for Mozambique.

Group	Variable	2017 (N=896)	2018 (N=960)	2019 (N=990)
GWP	SWB (0-10)	4.0 (2.0, 7.0)	5.0 (2.0, 7.0)	5.0 (2.0, 10.0)

(continued)

Group	Variable	2017 (N=896)	2018 (N=960)	2019 (N=990)
	Unknown	39	44	33
	Gender			
	Male	469 (52%)	566 (59%)	508 (51%)
	Female	427 (48%)	394 (41%)	482 (49%)
	Age	31 (22, 44)	29 (22, 40)	29 (21, 41)
	Income	471 (177, 1,178)	439 (146, 996)	431 (144, 1,069)
	Urbanicity			
	Rural Area	568 (63%)	530 (55%)	731 (74%)
	Small Town	220 (25%)	290 (30%)	200 (20%)
	Large City	17 (1.9%)	0 (0%)	9 (0.9%)
	Suburb	91 (10%)	140 (15%)	50 (5.1%)
30 days	FC Before	83 (21, 160)	71 (37, 116)	24 (9, 60)
	Unknown	50	0	20
	FC After	126 (65, 215)	73 (38, 120)	32 (11, 70)
	Unknown	50	0	20
	FCC	10 (3, 24)	18 (11, 28)	7 (3, 14)
	Unknown	50	0	20
	FCC (%)	18 (9, 33)	27 (18, 40)	30 (20, 52)
	Unknown	95	0	20
	Mean FAD Before	176 (60, 658)	149 (76, 240)	377 (177, 572)
	Unknown	87	0	20
	Mean FAD After	69 (18, 174)	157 (63, 235)	298 (116, 593)
	Unknown	50	0	20

(continued)

Group	Variable	2017 (N=896)	2018 (N=960)	2019 (N=990)
	FADC	-0.04 (-0.23, 0.00)	0.00 (-0.03, 0.03)	-0.02 (-0.14, 0.04)
	Unknown	87	0	20
	FADC (%)	-39 (-83, -2)	0 (-15, 35)	-12 (-37, 10)
	Unknown	87	0	20
90 days	FC Before	159 (92, 222)	109 (62, 152)	36 (15, 74)
	FC After	154 (98, 233)	102 (65, 160)	39 (16, 91)
	FCC	18 (7, 31)	17 (10, 24)	8 (3, 15)
	FCC (%)	14 (6, 25)	18 (12, 28)	25 (12, 34)
	Mean FAD Before	61 (20, 160)	93 (43, 196)	281 (129, 473)
	Mean FAD After	46 (15, 137)	101 (38, 189)	279 (102, 385)
	FADC	0.00 (-0.04, 0.01)	0.00 (-0.02, 0.01)	-0.02 (-0.11, 0.03)
	FADC (%)	-14 (-48, 19)	-1 (-13, 29)	-11 (-34, 14)
180 days	FC Before	143 (85, 224)	117 (77, 171)	82 (44, 163)
	FC After	151 (98, 227)	123 (82, 195)	83 (43, 147)
	FCC	16 (6, 26)	16 (10, 24)	15 (8, 26)
	FCC (%)	12 (6, 23)	14 (8, 24)	19 (10, 31)
	Mean FAD Before	57 (16, 174)	80 (29, 166)	131 (42, 265)
	Mean FAD After	53 (16, 141)	78 (26, 191)	133 (49, 233)
	FADC	0.00 (-0.03, 0.01)	0.00 (-0.01, 0.01)	0.01 (-0.02, 0.03)
	FADC (%)	-13 (-39, 18)	-4 (-18, 16)	5 (-15, 39)

[1] Median (IQR); n (%)

Table 16: Summary Statistics for Rwanda.

Group	Variable	2016 (N=992)	2017 (N=1000)	2018 (N=1000)	2019 (N=1000)
GWP	SWB (0-10)	3.00 (2.00, 5.00)	3.00 (2.00, 5.00)	3.00 (2.00, 5.00)	3.00 (1.00, 5.00)
	Unknown	5	17	14	19
	Gender				
	Male	435 (44%)	409 (41%)	394 (39%)	335 (34%)
	Female	557 (56%)	591 (59%)	606 (61%)	665 (67%)
	Age	30 (24, 40)	33 (25, 46)	33 (25, 46)	34 (26, 45)
	Income	330 (132, 776)	146 (61, 328)	237 (98, 547)	136 (45, 363)
	Urbanicity				
	Rural Area	544 (55%)	552 (55%)	760 (76%)	670 (67%)
	Small Town	304 (31%)	376 (38%)	150 (15%)	277 (28%)
	Large City	88 (8.9%)	56 (5.6%)	50 (5.0%)	40 (4.0%)
	Suburb	56 (5.6%)	16 (1.6%)	40 (4.0%)	13 (1.3%)
30 days	FC Before	12 (12, 12)	4 (1, 10)	62 (40, 95)	5 (2, 12)
	Unknown	991	254	0	100
	FC After	72 (72, 72)	11 (4, 20)	47 (33, 64)	1 (0, 7)
	Unknown	991	254	0	100
	FCC	4 (4, 4)	3 (1, 9)	27 (18, 39)	5 (2, 11)
	Unknown	991	254	0	100
	FCC (%)	30 (30, 30)	79 (63, 97)	46 (37, 61)	97 (86, 100)
	Unknown	991	300	0	100
	Mean FAD Before	666 (666, 666)	994 (739, 1,239)	183 (90, 312)	903 (718, 1,150)
	Unknown	991	299	0	100
	Mean FAD After	106 (106, 106)	806 (554, 1,038)	257 (156, 421)	1,101 (765, 1,273)

(continued)

Group	Variable	2016 (N=992)	2017 (N=1000)	2018 (N=1000)	2019 (N=1000)
	Unknown	991	262	0	165
	FADC	-0.55 (-0.55, -0.55)	-0.15 (-0.41, 0.10)	0.03 (0.00, 0.12)	0.13 (-0.22, 0.68)
	Unknown	991	308	0	195
	FADC (%)	-83 (-83, -83)	-16 (-40, 14)	20 (-1, 89)	18 (-23, 117)
	Unknown	991	308	0	195
90 days	FC Before	12 (12, 12)	17 (9, 31)	62 (47, 97)	39 (21, 63)
	Unknown	991	0	0	0
	FC After	72 (72, 72)	12 (6, 21)	78 (53, 102)	37 (21, 68)
	Unknown	991	0	0	0
	FCC	4 (4, 4)	11 (6, 24)	17 (10, 25)	11 (7, 18)
	Unknown	991	0	0	0
	FCC (%)	30 (30, 30)	73 (53, 88)	28 (19, 33)	29 (23, 38)
	Unknown	991	0	0	0
	Mean FAD Before	666 (666, 666)	510 (290, 679)	178 (81, 259)	217 (112, 362)
	Unknown	991	0	0	0
	Mean FAD After	106 (106, 106)	658 (461, 934)	137 (78, 210)	277 (117, 384)
	Unknown	991	0	0	0
	FADC	-0.55 (-0.55, -0.55)	0.09 (-0.04, 0.34)	-0.02 (-0.05, 0.00)	0.01 (-0.01, 0.05)
	Unknown	991	0	0	0
	FADC (%)	-83 (-83, -83)	22 (-5, 79)	-12 (-25, 6)	5 (-6, 17)
	Unknown	991	0	0	0
180 days	FC Before	12 (12, 12)	52 (28, 81)	64 (46, 94)	60 (42, 90)
	Unknown	991	0	0	0

(continued)

Group	Variable	2016 (N=992)	2017 (N=1000)	2018 (N=1000)	2019 (N=1000)
	FC After	84 (84, 84)	55 (26, 82)	77 (46, 102)	79 (45, 118)
	Unknown	991	0	0	0
	FCC	3 (3, 3)	9 (7, 15)	17 (11, 22)	9 (6, 12)
	Unknown	991	0	0	0
	FCC (%)	25 (25, 25)	24 (16, 35)	26 (19, 34)	15 (8, 27)
	Unknown	991	0	0	0
	Mean FAD Before	666 (666, 666)	181 (97, 290)	177 (86, 251)	145 (82, 238)
	Unknown	991	0	0	0
	Mean FAD After	95 (95, 95)	223 (102, 325)	143 (88, 233)	128 (58, 237)
	Unknown	991	0	0	0
	FADC	-0.57 (-0.57, -0.57)	-0.01 (-0.02, 0.04)	0.00 (-0.04, 0.01)	-0.01 (-0.03, 0.01)
	Unknown	991	0	0	0
	FADC (%)	-85 (-85, -85)	-4 (-14, 12)	0 (-16, 11)	-5 (-29, 4)
	Unknown	991	0	0	0

[1] Median (IQR); n (%)

Table 17: Summary Statistics for South Sudan.

Group	Variable	2016 (N=784)	2017 (N=616)
GWP	SWB (0-10)	2.00 (1.00, 5.00)	3.00 (1.00, 4.00)
	Unknown	15	27
	Gender		
	Male	368 (47%)	272 (44%)
	Female	416 (53%)	344 (56%)

(continued)

Group	Variable	2016 (N=784)	2017 (N=616)
	Age	29 (20, 40)	30 (21, 40)
	Income	292 (39, 1,089)	1,151 (101, 4,009)
	Urbanicity		
	Rural Area	506 (65%)	347 (56%)
	Small Town	187 (24%)	234 (38%)
	Large City	64 (8.2%)	16 (2.6%)
	Suburb	27 (3.4%)	19 (3.1%)
30 days	FC Before	NA (NA, NA)	44 (12, 91)
	Unknown	784	172
	FC After	NA (NA, NA)	82 (13, 150)
	Unknown	784	172
	FCC	NA (NA, NA)	16 (3, 37)
	Unknown	784	172
	FCC (%)	NA (NA, NA)	42 (28, 82)
	Unknown	784	188
	Mean FAD Before	NA (NA, NA)	452 (252, 869)
	Unknown	784	188
	Mean FAD After	NA (NA, NA)	226 (80, 611)
	Unknown	784	196
	FADC	NA (NA, NA)	-0.11 (-0.48, 0.07)
	Unknown	784	215
	FADC (%)	NA (NA, NA)	-26 (-77, 29)
	Unknown	784	215

(continued)

Group	Variable	2016 (N=784)	2017 (N=616)
90 days	FC Before	NA (NA, NA)	43 (6, 105)
	Unknown	784	8
	FC After	NA (NA, NA)	27 (2, 90)
	Unknown	784	8
	FCC	NA (NA, NA)	14 (4, 38)
	Unknown	784	8
	FCC (%)	NA (NA, NA)	58 (29, 80)
	Unknown	784	8
	Mean FAD Before	NA (NA, NA)	418 (188, 921)
	Unknown	784	8
	Mean FAD After	NA (NA, NA)	565 (168, 1,080)
	Unknown	784	16
	FADC	NA (NA, NA)	0.03 (-0.06, 0.14)
	Unknown	784	16
	FADC (%)	NA (NA, NA)	7 (-11, 58)
	Unknown	784	16
180 days	FC Before	NA (NA, NA)	55 (9, 128)
	Unknown	784	0
	FC After	NA (NA, NA)	36 (7, 102)
	Unknown	784	0
	FCC	NA (NA, NA)	20 (6, 38)
	Unknown	784	0
	FCC (%)	NA (NA, NA)	44 (27, 61)

(continued)

Group	Variable	2016 (N=784)	2017 (N=616)
	Unknown	784	0
	Mean FAD Before	NA (NA, NA)	358 (149, 806)
	Unknown	784	0
	Mean FAD After	NA (NA, NA)	488 (178, 894)
	Unknown	784	0
	FADC	NA (NA, NA)	0.09 (0.01, 0.19)
	Unknown	784	0
	FADC (%)	NA (NA, NA)	36 (11, 83)
	Unknown	784	0

[1] Median (IQR); n (%)

Table 18: Summary Statistics for Tanzania.

Group	Variable	2016 (N=968)	2017 (N=960)	2018 (N=970)	2019 (N=1000)
GWP	SWB (0-10)	3.00 (1.00, 5.00)	3.00 (1.00, 5.00)	4.00 (1.00, 5.00)	3.00 (1.00, 5.00)
	Unknown	2	4	9	22
	Gender				
	Male	381 (39%)	419 (44%)	418 (43%)	400 (40%)
	Female	587 (61%)	541 (56%)	552 (57%)	600 (60%)
	Age	32 (23, 46)	32 (23, 45)	33 (23, 46)	32 (24, 45)
	Income	325 (116, 812)	608 (228, 1,520)	478 (215, 1,076)	405 (169, 845)
	Urbanicity				
	Rural Area	377 (39%)	367 (38%)	371 (38%)	374 (37%)
	Small Town	404 (42%)	376 (39%)	375 (39%)	495 (50%)

(continued)

Group	Variable	2016 (N=968)	2017 (N=960)	2018 (N=970)	2019 (N=1000)
	Large City	112 (12%)	113 (12%)	85 (8.8%)	66 (6.6%)
	Suburb	75 (7.7%)	104 (11%)	139 (14%)	65 (6.5%)
30 days	FC Before	NA (NA, NA)	48 (16, 88)	26 (6, 78)	9 (3, 26)
	Unknown	968	48	100	56
	FC After	NA (NA, NA)	31 (11, 87)	62 (35, 136)	6 (1, 21)
	Unknown	968	48	100	56
	FCC	NA (NA, NA)	15 (8, 29)	4 (1, 12)	5 (2, 15)
	Unknown	968	48	100	56
	FCC (%)	NA (NA, NA)	43 (24, 65)	20 (13, 30)	63 (46, 82)
	Unknown	968	48	114	72
	Mean FAD Before	NA (NA, NA)	308 (150, 585)	382 (155, 882)	811 (515, 1,113)
	Unknown	968	48	104	64
	Mean FAD After	NA (NA, NA)	450 (182, 772)	187 (65, 372)	870 (599, 1,101)
	Unknown	968	48	100	64
	FADC	NA (NA, NA)	0.09 (-0.02, 0.23)	-0.18 (-0.54, -0.01)	0.08 (-0.10, 0.19)
	Unknown	968	48	114	80
	FADC (%)	NA (NA, NA)	27 (-13, 96)	-47 (-71, -8)	9 (-12, 30)
	Unknown	968	48	114	80
90 days	FC Before	NA (NA, NA)	57 (24, 106)	22 (5, 87)	18 (7, 49)
	Unknown	968	32	24	16
	FC After	NA (NA, NA)	37 (13, 92)	76 (35, 142)	16 (6, 52)
	Unknown	968	32	24	16
	FCC	NA (NA, NA)	17 (9, 41)	3 (1, 11)	5 (2, 12)

(continued)

Group	Variable	2016 (N=968)	2017 (N=960)	2018 (N=970)	2019 (N=1000)
	Unknown	968	32	24	16
	FCC (%)	NA (NA, NA)	42 (21, 64)	16 (10, 27)	35 (20, 53)
	Unknown	968	48	44	16
	Mean FAD Before	NA (NA, NA)	240 (84, 485)	406 (159, 981)	557 (328, 915)
	Unknown	968	48	34	16
	Mean FAD After	NA (NA, NA)	384 (170, 725)	174 (62, 331)	579 (346, 965)
	Unknown	968	32	24	16
	FADC	NA (NA, NA)	0.06 (0.00, 0.22)	-0.19 (-0.57, -0.03)	0.03 (-0.05, 0.15)
	Unknown	968	48	44	16
	FADC (%)	NA (NA, NA)	33 (1, 121)	-51 (-71, -17)	5 (-12, 25)
	Unknown	968	48	44	16
180 days	FC Before	NA (NA, NA)	63 (24, 117)	42 (10, 102)	44 (17, 104)
	Unknown	968	0	0	0
	FC After	NA (NA, NA)	43 (13, 103)	75 (28, 135)	37 (14, 97)
	Unknown	968	0	0	0
	FCC	NA (NA, NA)	19 (10, 40)	3 (1, 9)	7 (3, 16)
	Unknown	968	0	0	0
	FCC (%)	NA (NA, NA)	44 (24, 65)	13 (7, 18)	20 (11, 43)
	Unknown	968	0	0	0
	Mean FAD Before	NA (NA, NA)	227 (81, 477)	353 (152, 736)	329 (128, 623)
	Unknown	968	0	0	0
	Mean FAD After	NA (NA, NA)	344 (139, 668)	181 (79, 409)	390 (173, 741)
	Unknown	968	0	0	0

(continued)

Group	Variable	2016 (N=968)	2017 (N=960)	2018 (N=970)	2019 (N=1000)
	FADC	NA (NA, NA)	0.10 (0.01, 0.21)	-0.11 (-0.28, -0.02)	0.02 (-0.02, 0.12)
	Unknown	968	0	0	0
	FADC (%)	NA (NA, NA)	42 (5, 114)	-33 (-52, -13)	7 (-7, 34)
	Unknown	968	0	0	0

[1] Median (IQR); n (%)

Table 19: Summary Statistics for Uganda.

Group	Variable	2016 (N=656)	2017 (N=960)	2018 (N=1000)	2019 (N=1000)
GWP	SWB (0-10)	5.0 (2.0, 6.0)	4.0 (2.0, 5.0)	4.0 (2.0, 6.0)	5.0 (3.0, 7.0)
	Unknown	4	72	21	20
	Gender				
	Male	316 (48%)	402 (42%)	460 (46%)	468 (47%)
	Female	340 (52%)	558 (58%)	540 (54%)	532 (53%)
	Age	28 (21, 42)	28 (22, 40)	28 (22, 39)	25 (20, 33)
	Income	213 (71, 532)	499 (200, 1,249)	557 (174, 1,448)	610 (229, 1,373)
	Urbanicity				
	Rural Area	374 (57%)	542 (56%)	540 (54%)	319 (32%)
	Small Town	275 (42%)	385 (40%)	388 (39%)	524 (52%)
	Large City	1 (0.2%)	8 (0.8%)	2 (0.2%)	75 (7.5%)
	Suburb	6 (0.9%)	25 (2.6%)	70 (7.0%)	82 (8.2%)
30 days	FC Before	9 (9, 13)	42 (17, 107)	33 (12, 72)	33 (12, 73)
	Unknown	616	0	116	188
	FC After	26 (19, 28)	61 (40, 103)	45 (23, 80)	36 (15, 62)

(continued)

Group	Variable	2016 (N=656)	2017 (N=960)	2018 (N=1000)	2019 (N=1000)
	Unknown	616	0	116	188
	FCC	7 (4, 8)	22 (7, 50)	14 (4, 32)	19 (7, 42)
	Unknown	616	0	116	188
	FCC (%)	60 (40, 74)	53 (35, 66)	48 (36, 62)	67 (46, 92)
	Unknown	616	0	152	196
	Mean FAD Before	515 (418, 521)	457 (184, 808)	331 (173, 614)	375 (163, 749)
	Unknown	616	0	144	196
	Mean FAD After	379 (289, 421)	191 (103, 378)	250 (129, 441)	452 (212, 711)
	Unknown	616	0	124	196
	FADC	-0.10 (-0.13, 0.01)	-0.19 (-0.59, 0.05)	-0.09 (-0.30, 0.06)	-0.02 (-0.28, 0.25)
	Unknown	616	0	152	204
	FADC (%)	-26 (-33, 2)	-37 (-81, 36)	-27 (-62, 37)	-12 (-56, 147)
	Unknown	616	0	152	204
90 days	FC Before	25 (10, 44)	89 (49, 140)	71 (42, 119)	43 (21, 81)
	Unknown	280	0	0	16
	FC After	99 (54, 175)	59 (41, 107)	76 (43, 121)	61 (28, 90)
	Unknown	280	0	0	16
	FCC	5 (3, 11)	41 (18, 60)	20 (12, 35)	15 (7, 27)
	Unknown	280	0	0	16
	FCC (%)	27 (17, 33)	45 (32, 62)	34 (20, 44)	39 (25, 54)
	Unknown	304	0	0	16
	Mean FAD Before	515 (310, 772)	129 (62, 273)	129 (73, 248)	212 (121, 339)
	Unknown	296	0	0	16

(continued)

Group	Variable	2016 (N=656)	2017 (N=960)	2018 (N=1000)	2019 (N=1000)
	Mean FAD After	90 (49, 193)	187 (85, 325)	113 (65, 219)	210 (105, 392)
	Unknown	280	0	0	24
	FADC	-0.34 (-0.67, -0.17)	0.03 (-0.02, 0.09)	0.00 (-0.04, 0.03)	-0.02 (-0.09, 0.07)
	Unknown	296	0	0	24
	FADC (%)	-76 (-89, -56)	36 (-11, 79)	-2 (-34, 25)	-15 (-38, 49)
	Unknown	296	0	0	24
180 days	FC Before	25 (10, 44)	58 (33, 116)	67 (41, 124)	57 (29, 100)
	Unknown	280	0	0	0
	FC After	71 (42, 136)	44 (19, 92)	82 (41, 120)	105 (62, 155)
	Unknown	280	0	0	0
	FCC	6 (3, 11)	30 (11, 45)	16 (8, 30)	9 (4, 13)
	Unknown	280	0	0	0
	FCC (%)	28 (22, 42)	43 (32, 65)	26 (17, 39)	15 (10, 21)
	Unknown	304	0	0	0
	Mean FAD Before	515 (310, 772)	186 (80, 339)	143 (76, 243)	166 (80, 258)
	Unknown	296	0	0	0
	Mean FAD After	101 (72, 216)	251 (100, 459)	108 (61, 217)	98 (48, 204)
	Unknown	280	0	0	0
	FADC	-0.33 (-0.67, -0.17)	0.04 (0.00, 0.14)	-0.01 (-0.05, 0.02)	-0.05 (-0.08, -0.03)
	Unknown	296	0	0	0
	FADC (%)	-75 (-88, -48)	40 (-1, 94)	-10 (-34, 21)	-31 (-45, -23)
	Unknown	296	0	0	0

[1] Median (IQR); n (%)

Table 20: Summary Statistics for Zimbabwe.

Group	Variable	2016 (N=936)	2017 (N=944)	2018 (N=980)	2019 (N=1082)
GWP	SWB (0-10)	4.00 (1.00, 5.00)	4.00 (2.00, 5.00)	4.00 (2.00, 5.00)	2.00 (0.00, 5.00)
	Unknown	18	13	4	9
	Gender				
	Male	306 (33%)	366 (39%)	392 (40%)	489 (45%)
	Female	630 (67%)	578 (61%)	588 (60%)	593 (55%)
	Age	31 (23, 43)	33 (24, 46)	32 (23, 44)	33 (23, 47)
	Income	560 (168, 1,493)	906 (340, 2,264)	978 (380, 2,282)	NA (NA, NA)
	Unknown	0	0	0	1,082
	Urbanicity				
	Rural Area	477 (51%)	514 (54%)	551 (56%)	620 (57%)
	Small Town	161 (17%)	141 (15%)	157 (16%)	135 (12%)
	Large City	36 (3.8%)	7 (0.7%)	20 (2.0%)	78 (7.2%)
	Suburb	262 (28%)	282 (30%)	252 (26%)	249 (23%)
30 days	FC Before	NA (NA, NA)	96 (57, 129)	99 (61, 135)	65 (28, 104)
	Unknown	936	11	0	0
	FC After	NA (NA, NA)	73 (43, 138)	116 (66, 153)	58 (25, 95)
	Unknown	936	11	0	0
	FCC	NA (NA, NA)	21 (14, 39)	13 (9, 17)	11 (8, 25)
	Unknown	936	11	0	0
	FCC (%)	NA (NA, NA)	29 (15, 67)	14 (9, 23)	27 (13, 43)
	Unknown	936	11	0	0
	Mean FAD Before	NA (NA, NA)	124 (70, 193)	96 (57, 189)	194 (93, 303)
	Unknown	936	11	0	0

(continued)

Group	Variable	2016 (N=936)	2017 (N=944)	2018 (N=980)	2019 (N=1082)
	Mean FAD After	NA (NA, NA)	136 (55, 407)	73 (44, 146)	186 (120, 370)
	Unknown	936	17	0	0
	FADC	NA (NA, NA)	0.01 (-0.03, 0.31)	0.00 (-0.02, 0.01)	0.03 (-0.01, 0.10)
	Unknown	936	17	0	0
	FADC (%)	NA (NA, NA)	11 (-34, 135)	-6 (-26, 9)	17 (-5, 51)
	Unknown	936	17	0	0
90 days	FC Before	NA (NA, NA)	96 (55, 127)	112 (64, 156)	97 (49, 135)
	Unknown	936	0	0	0
	FC After	NA (NA, NA)	107 (68, 149)	120 (70, 153)	66 (33, 106)
	Unknown	936	0	0	0
	FCC	NA (NA, NA)	12 (5, 22)	14 (11, 18)	22 (15, 36)
	Unknown	936	0	0	0
	FCC (%)	NA (NA, NA)	16 (7, 33)	14 (8, 21)	35 (15, 51)
	Unknown	936	0	0	0
	Mean FAD Before	NA (NA, NA)	125 (77, 210)	78 (41, 144)	103 (63, 197)
	Unknown	936	0	0	0
	Mean FAD After	NA (NA, NA)	85 (51, 159)	75 (43, 143)	160 (92, 324)
	Unknown	936	0	0	0
	FADC	NA (NA, NA)	-0.03 (-0.09, 0.02)	0.00 (-0.01, 0.01)	0.06 (0.01, 0.14)
	Unknown	936	0	0	0
	FADC (%)	NA (NA, NA)	-35 (-54, 14)	2 (-9, 11)	56 (17, 91)
	Unknown	936	0	0	0
180 days	FC Before	NA (NA, NA)	48 (20, 73)	104 (57, 149)	99 (54, 140)

(continued)

Group	Variable	2016 (N=936)	2017 (N=944)	2018 (N=980)	2019 (N=1082)
	Unknown	936	0	0	0
	FC After	NA (NA, NA)	21 (8, 53)	89 (49, 142)	69 (36, 116)
	Unknown	936	0	0	0
	FCC	NA (NA, NA)	14 (8, 34)	17 (8, 24)	23 (16, 37)
	Unknown	936	0	0	0
	FCC (%)	NA (NA, NA)	47 (31, 67)	18 (11, 25)	31 (17, 46)
	Unknown	936	0	0	0
	Mean FAD Before	NA (NA, NA)	266 (159, 435)	90 (52, 151)	97 (56, 181)
	Unknown	936	0	0	0
	Mean FAD After	NA (NA, NA)	459 (238, 668)	120 (65, 195)	148 (84, 298)
	Unknown	936	0	0	0
	FADC	NA (NA, NA)	0.14 (0.05, 0.27)	0.01 (-0.01, 0.04)	0.05 (0.02, 0.11)
	Unknown	936	0	0	0
	FADC (%)	NA (NA, NA)	40 (18, 118)	25 (-11, 42)	54 (26, 87)
	Unknown	936	0	0	0

[1] Median (IQR); n (%)

11.6.2 Middle Africa (A-Z)

Table 21: Summary Statistics for Cameroon.

Group	Variable	2016 (N=944)	2017 (N=1000)	2018 (N=990)	2019 (N=980)
GWP	SWB (0-10)	5.0 (4.0, 6.0)	5.0 (3.0, 7.0)	5.0 (3.0, 7.0)	5.0 (3.0, 6.0)
	Unknown	20	47	54	23

(continued)

Group	Variable	2016 (N=944)	2017 (N=1000)	2018 (N=990)	2019 (N=980)
	Gender				
	Male	444 (47%)	457 (46%)	500 (51%)	523 (53%)
	Female	500 (53%)	543 (54%)	490 (49%)	457 (47%)
	Age	29 (22, 40)	30 (22, 41)	28 (21, 38)	28 (21, 37)
	Income	640 (282, 1,381)	740 (265, 1,765)	970 (404, 1,940)	818 (364, 1,963)
	Urbanicity				
	Rural Area	0 (NA%)	344 (34%)	300 (30%)	111 (11%)
	Small Town	0 (NA%)	304 (30%)	320 (32%)	419 (43%)
	Large City	0 (NA%)	312 (31%)	280 (28%)	440 (45%)
	Suburb	0 (NA%)	40 (4.0%)	90 (9.1%)	10 (1.0%)
	Unknown	944	0	0	0
30 days	FC Before	NA (NA, NA)	144 (52, 144)	5 (0, 22)	6 (1, 43)
	Unknown	944	3	430	284
	FC After	NA (NA, NA)	97 (60, 97)	0 (0, 22)	1 (0, 13)
	Unknown	944	3	430	284
	FCC	NA (NA, NA)	53 (12, 53)	4 (0, 14)	4 (1, 29)
	Unknown	944	3	430	284
	FCC (%)	NA (NA, NA)	37 (37, 37)	94 (57, 100)	98 (44, 100)
	Unknown	944	11	505	314
	Mean FAD Before	NA (NA, NA)	39 (39, 145)	824 (359, 1,300)	1,106 (512, 1,263)
	Unknown	944	11	504	304
	Mean FAD After	NA (NA, NA)	97 (97, 163)	999 (413, 1,421)	1,036 (625, 1,338)
	Unknown	944	3	555	495

(continued)

Group	Variable	2016 (N=944)	2017 (N=1000)	2018 (N=990)	2019 (N=980)
	FADC	NA (NA, NA)	0.06 (0.02, 0.06)	0.30 (-0.04, 0.38)	0.08 (-0.20, 0.53)
	Unknown	944	11	609	524
	FADC (%)	NA (NA, NA)	151 (20, 151)	39 (-8, 74)	7 (-23, 78)
	Unknown	944	11	609	524
90 days	FC Before	NA (NA, NA)	167 (112, 167)	21 (2, 96)	5 (0, 54)
	Unknown	944	0	0	10
	FC After	NA (NA, NA)	134 (103, 134)	35 (0, 97)	75 (23, 135)
	Unknown	944	0	0	10
	FCC	NA (NA, NA)	35 (15, 37)	5 (1, 18)	1 (0, 15)
	Unknown	944	0	0	10
	FCC (%)	NA (NA, NA)	22 (18, 22)	53 (19, 80)	23 (12, 37)
	Unknown	944	0	20	220
	Mean FAD Before	NA (NA, NA)	35 (33, 64)	697 (133, 1,202)	1,067 (314, 1,392)
	Unknown	944	0	0	128
	Mean FAD After	NA (NA, NA)	64 (64, 80)	406 (125, 1,038)	431 (101, 661)
	Unknown	944	0	80	30
	FADC	NA (NA, NA)	0.03 (0.02, 0.03)	0.00 (-0.34, 0.24)	-0.19 (-0.75, -0.03)
	Unknown	944	0	80	138
	FADC (%)	NA (NA, NA)	82 (19, 82)	7 (-34, 54)	-52 (-81, -3)
	Unknown	944	0	80	138
180 days	FC Before	NA (NA, NA)	162 (108, 162)	93 (12, 180)	100 (7, 154)
	Unknown	944	0	0	0
	FC After	NA (NA, NA)	153 (113, 153)	114 (70, 222)	98 (17, 174)

(continued)

Group	Variable	2016 (N=944)	2017 (N=1000)	2018 (N=990)	2019 (N=980)
	Unknown	944	0	0	0
	FCC	NA (NA, NA)	21 (5, 21)	5 (2, 10)	10 (0, 23)
	Unknown	944	0	0	0
	FCC (%)	NA (NA, NA)	13 (10, 13)	9 (4, 37)	12 (6, 24)
	Unknown	944	0	0	56
	Mean FAD Before	NA (NA, NA)	38 (38, 67)	282 (49, 852)	220 (63, 864)
	Unknown	944	0	0	30
	Mean FAD After	NA (NA, NA)	58 (58, 67)	91 (32, 619)	294 (50, 697)
	Unknown	944	0	0	0
	FADC	NA (NA, NA)	0.02 (0.00, 0.02)	-0.01 (-0.08, 0.02)	-0.01 (-0.19, 0.01)
	Unknown	944	0	0	30
	FADC (%)	NA (NA, NA)	53 (-7, 53)	-18 (-36, 21)	-5 (-23, 27)
	Unknown	944	0	0	30

[1] Median (IQR); n (%)

Table 22: Summary Statistics for Central African Republic.

Group	Variable	2017 (N=1000)
GWP	SWB (0-10)	3.0 (2.0, 5.0)
	Unknown	22
	Gender	
	Male	466 (47%)
	Female	534 (53%)

(continued)

Group	Variable	2017 (N=1000)
	Age	30 (22, 41)
	Income	217 (90, 569)
	Urbanicity	
	Rural Area	259 (26%)
	Small Town	399 (40%)
	Large City	296 (30%)
	Suburb	46 (4.6%)
30 days	FC Before	3 (2, 9)
	Unknown	247
	FC After	129 (115, 187)
	Unknown	247
	FCC	0 (0, 1)
	Unknown	247
	FCC (%)	9 (5, 44)
	Unknown	271
	Mean FAD Before	1,268 (1,046, 1,297)
	Unknown	271
	Mean FAD After	220 (107, 229)
	Unknown	263
	FADC	-1.04 (-1.10, -0.83)
	Unknown	271
	FADC (%)	-84 (-93, -77)
	Unknown	271

(continued)

Group	Variable	2017 (N=1000)
90 days	FC Before	60 (24, 113)
	FC After	134 (108, 200)
	FCC	7 (2, 22)
	FCC (%)	14 (7, 31)
	Unknown	8
	Mean FAD Before	543 (109, 849)
	Unknown	8
	Mean FAD After	165 (29, 286)
	Unknown	8
	FADC	-0.35 (-0.71, -0.02)
	Unknown	8
	FADC (%)	-73 (-83, -27)
	Unknown	8
180 days	FC Before	220 (156, 261)
	FC After	221 (135, 260)
	FCC	31 (16, 40)
	FCC (%)	13 (6, 25)
	Unknown	8
	Mean FAD Before	19 (8, 80)
	Unknown	8
	Mean FAD After	18 (10, 206)
	Unknown	8
	FADC	0.01 (0.00, 0.13)

(continued)

Group	Variable	2017 (N=1000)
	Unknown	8
	FADC (%)	92 (17, 160)
	Unknown	8

[1] Median (IQR); n (%)

Table 23: Summary Statistics for Chad.

Group	Variable	2016 (N=1000)	2017 (N=1000)	2018 (N=990)	2019 (N=1111)
GWP	SWB (0-10)	4.0 (3.0, 5.0)	4.0 (3.0, 6.0)	5.0 (2.0, 7.0)	4.0 (2.0, 7.0)
	Unknown	14	49	116	36
	Gender				
	Male	559 (56%)	637 (64%)	699 (71%)	733 (66%)
	Female	441 (44%)	363 (36%)	291 (29%)	378 (34%)
	Age	28 (20, 39)	30 (22, 40)	30 (22, 40)	30 (22, 40)
	Income	361 (173, 775)	534 (214, 1,389)	462 (187, 1,011)	387 (179, 851)
	Urbanicity				
	Rural Area	120 (12%)	248 (25%)	240 (24%)	329 (30%)
	Small Town	680 (68%)	576 (58%)	560 (57%)	603 (54%)
	Large City	128 (13%)	104 (10%)	160 (16%)	146 (13%)
	Suburb	72 (7.2%)	72 (7.2%)	30 (3.0%)	33 (3.0%)
30 days	FC Before	NA (NA, NA)	0 (0, 2)	40 (4, 111)	36 (3, 100)
	Unknown	1,000	78	70	0
	FC After	NA (NA, NA)	0 (0, 1)	50 (6, 100)	50 (6, 118)
	Unknown	1,000	78	70	0

(continued)

Group	Variable	2016 (N=1000)	2017 (N=1000)	2018 (N=990)	2019 (N=1111)
	FCC	NA (NA, NA)	0 (0, 1)	13 (2, 41)	9 (1, 20)
	Unknown	1,000	78	70	0
	FCC (%)	NA (NA, NA)	61 (37, 86)	43 (21, 61)	24 (16, 35)
	Unknown	1,000	386	105	20
	Mean FAD Before	NA (NA, NA)	1,332 (980, 1,505)	310 (130, 935)	288 (99, 973)
	Unknown	1,000	298	105	10
	Mean FAD After	NA (NA, NA)	1,382 (1,167, 1,466)	268 (135, 758)	227 (93, 805)
	Unknown	1,000	254	80	10
	FADC	NA (NA, NA)	0.02 (-0.08, 0.21)	-0.03 (-0.26, 0.07)	-0.06 (-0.16, -0.01)
	Unknown	1,000	324	105	10
	FADC (%)	NA (NA, NA)	1 (-6, 24)	-11 (-49, 21)	-24 (-33, -3)
	Unknown	1,000	324	105	10
90 days	FC Before	NA (NA, NA)	1 (0, 5)	23 (3, 94)	36 (3, 94)
	Unknown	1,000	0	0	0
	FC After	NA (NA, NA)	0 (0, 2)	30 (3, 71)	49 (5, 105)
	Unknown	1,000	0	0	0
	FCC	NA (NA, NA)	0 (0, 2)	10 (2, 31)	11 (1, 20)
	Unknown	1,000	0	0	0
	FCC (%)	NA (NA, NA)	62 (17, 85)	43 (20, 64)	32 (19, 42)
	Unknown	1,000	204	60	20
	Mean FAD Before	NA (NA, NA)	1,166 (815, 1,430)	364 (143, 890)	259 (105, 1,009)
	Unknown	1,000	148	30	10
	Mean FAD After	NA (NA, NA)	1,320 (1,059, 1,389)	372 (164, 803)	235 (115, 886)

(continued)

Group	Variable	2016 (N=1000)	2017 (N=1000)	2018 (N=990)	2019 (N=1111)
	Unknown	1,000	120	20	10
	FADC	NA (NA, NA)	0.10 (-0.15, 0.38)	0.01 (-0.12, 0.11)	-0.02 (-0.11, 0.02)
	Unknown	1,000	160	30	10
	FADC (%)	NA (NA, NA)	9 (-13, 48)	7 (-28, 40)	-13 (-23, 8)
	Unknown	1,000	160	30	10
180 days	FC Before	NA (NA, NA)	5 (1, 21)	6 (1, 36)	16 (1, 58)
	Unknown	1,000	0	0	0
	FC After	NA (NA, NA)	6 (1, 33)	1 (0, 14)	17 (1, 59)
	Unknown	1,000	0	0	0
	FCC	NA (NA, NA)	1 (0, 8)	3 (0, 13)	5 (0, 18)
	Unknown	1,000	0	0	0
	FCC (%)	NA (NA, NA)	28 (11, 44)	74 (30, 95)	37 (18, 54)
	Unknown	1,000	42	130	50
	Mean FAD Before	NA (NA, NA)	878 (438, 1,279)	752 (400, 1,168)	501 (216, 1,125)
	Unknown	1,000	34	110	20
	Mean FAD After	NA (NA, NA)	847 (407, 1,208)	1,049 (534, 1,445)	583 (217, 1,164)
	Unknown	1,000	32	146	30
	FADC	NA (NA, NA)	-0.04 (-0.21, 0.06)	0.16 (-0.02, 0.56)	0.01 (-0.09, 0.10)
	Unknown	1,000	34	146	30
	FADC (%)	NA (NA, NA)	-8 (-21, 15)	25 (-12, 77)	2 (-10, 42)
	Unknown	1,000	34	146	30

[1] Median (IQR); n (%)

Table 24: Summary Statistics for Congo (Kinshasa).

Group	Variable	2017 (N=1000)
GWP	SWB (0-10)	5.0 (3.0, 6.0)
	Unknown	21
	Gender	
	Male	630 (63%)
	Female	370 (37%)
	Age	29 (22, 40)
	Income	565 (205, 1,432)
	Urbanicity	
	Rural Area	168 (17%)
	Small Town	456 (46%)
	Large City	320 (32%)
	Suburb	56 (5.6%)
30 days	FC Before	3 (0, 35)
	Unknown	442
	FC After	11 (1, 177)
	Unknown	442
	FCC	1 (0, 8)
	Unknown	442
	FCC (%)	94 (7, 100)
	Unknown	547
	Mean FAD Before	1,119 (605, 1,332)
	Unknown	483
	Mean FAD After	744 (86, 1,133)

(continued)

Group	Variable	2017 (N=1000)
	Unknown	487
	FADC	-0.61 (-1.04, 0.12)
	Unknown	696
	FADC (%)	-87 (-97, 22)
	Unknown	696
90 days	FC Before	85 (3, 187)
	Unknown	71
	FC After	88 (15, 224)
	Unknown	71
	FCC	6 (0, 32)
	Unknown	71
	FCC (%)	21 (5, 58)
	Unknown	152
	Mean FAD Before	398 (87, 1,088)
	Unknown	103
	Mean FAD After	217 (30, 771)
	Unknown	79
	FADC	-0.08 (-0.69, 0.12)
	Unknown	111
	FADC (%)	-41 (-78, 70)
	Unknown	111
180 days	FC Before	147 (39, 234)
	Unknown	8

(continued)

Group	Variable	2017 (N=1000)
	FC After	145 (38, 237)
	Unknown	8
	FCC	17 (3, 43)
	Unknown	8
	FCC (%)	20 (6, 64)
	Unknown	56
	Mean FAD Before	118 (35, 477)
	Unknown	32
	Mean FAD After	120 (28, 624)
	Unknown	8
	FADC	0.00 (-0.21, 0.04)
	Unknown	32
	FADC (%)	3 (-41, 55)
	Unknown	32

[1] Median (IQR); n (%)

Table 25: Summary Statistics for Congo (Brazzaville).

Group	Variable	2016 (N=1000)	2017 (N=984)	2018 (N=1000)	2019 (N=1090)
GWP	SWB (0-10)	4.0 (2.8, 5.0)	5.0 (3.0, 7.0)	5.0 (3.0, 8.0)	5.0 (3.0, 8.0)
	Unknown	16	76	81	41
	Gender				
	Male	482 (48%)	507 (52%)	603 (60%)	590 (54%)
	Female	518 (52%)	477 (48%)	397 (40%)	500 (46%)

(continued)

Group	Variable	2016 (N=1000)	2017 (N=984)	2018 (N=1000)	2019 (N=1090)
	Age	33 (24, 46)	32 (24, 45)	32 (23, 45)	31 (23, 44)
	Income	1,105 (483, 2,038)	1,266 (572, 2,675)	825 (263, 1,928)	1,053 (530, 1,943)
	Urbanicity				
	Rural Area	56 (5.6%)	64 (6.5%)	100 (10%)	26 (2.4%)
	Small Town	360 (36%)	352 (36%)	330 (33%)	405 (37%)
	Large City	568 (57%)	560 (57%)	560 (56%)	635 (58%)
	Suburb	16 (1.6%)	8 (0.8%)	10 (1.0%)	24 (2.2%)
30 days	FC Before	NA (NA, NA)	3 (2, 12)	1 (0, 63)	0 (0, 48)
	Unknown	1,000	385	391	175
	FC After	NA (NA, NA)	18 (1, 31)	34 (24, 73)	31 (17, 65)
	Unknown	1,000	385	391	175
	FCC	NA (NA, NA)	2 (0, 7)	0 (0, 6)	0 (0, 14)
	Unknown	1,000	385	391	175
	FCC (%)	NA (NA, NA)	88 (20, 100)	35 (27, 46)	36 (12, 59)
	Unknown	1,000	393	595	528
	Mean FAD Before	NA (NA, NA)	1,108 (950, 1,162)	1,055 (374, 1,228)	817 (382, 1,438)
	Unknown	1,000	385	515	378
	Mean FAD After	NA (NA, NA)	750 (558, 1,247)	566 (360, 670)	546 (350, 736)
	Unknown	1,000	425	395	189
	FADC	NA (NA, NA)	-0.01 (-0.73, 0.10)	-0.61 (-0.72, -0.02)	-0.54 (-1.16, -0.03)
	Unknown	1,000	453	519	382
	FADC (%)	NA (NA, NA)	-1 (-66, 9)	-61 (-68, -8)	-52 (-82, -10)
	Unknown	1,000	453	519	382

(continued)

Group	Variable	2016 (N=1000)	2017 (N=984)	2018 (N=1000)	2019 (N=1090)
90 days	FC Before	NA (NA, NA)	9 (4, 82)	29 (0, 75)	41 (6, 127)
	Unknown	1,000	208	120	0
	FC After	NA (NA, NA)	50 (32, 131)	33 (17, 75)	43 (19, 115)
	Unknown	1,000	208	120	0
	FCC	NA (NA, NA)	3 (1, 14)	7 (0, 11)	11 (3, 26)
	Unknown	1,000	208	120	0
	FCC (%)	NA (NA, NA)	31 (23, 41)	25 (16, 35)	28 (21, 46)
	Unknown	1,000	216	290	155
	Mean FAD Before	NA (NA, NA)	955 (328, 1,088)	582 (333, 749)	448 (93, 706)
	Unknown	1,000	216	220	92
	Mean FAD After	NA (NA, NA)	445 (218, 585)	610 (312, 844)	512 (216, 702)
	Unknown	1,000	208	120	0
	FADC	NA (NA, NA)	-0.56 (-0.70, 0.00)	-0.01 (-0.18, 0.03)	0.02 (-0.01, 0.10)
	Unknown	1,000	216	220	92
	FADC (%)	NA (NA, NA)	-61 (-69, 1)	-3 (-18, 8)	10 (-12, 31)
	Unknown	1,000	216	220	92
180 days	FC Before	NA (NA, NA)	9 (5, 99)	45 (21, 102)	53 (25, 147)
	Unknown	1,000	184	0	0
	FC After	NA (NA, NA)	55 (33, 140)	48 (25, 91)	53 (24, 140)
	Unknown	1,000	184	0	0
	FCC	NA (NA, NA)	2 (1, 13)	12 (1, 17)	10 (6, 21)
	Unknown	1,000	184	0	0
	FCC (%)	NA (NA, NA)	30 (18, 38)	32 (20, 48)	26 (13, 35)

(continued)

Group	Variable	2016 (N=1000)	2017 (N=984)	2018 (N=1000)	2019 (N=1090)
	Unknown	1,000	192	100	0
	Mean FAD Before	NA (NA, NA)	953 (305, 1,059)	488 (171, 718)	455 (70, 667)
	Unknown	1,000	192	30	0
	Mean FAD After	NA (NA, NA)	381 (105, 575)	527 (212, 712)	481 (92, 685)
	Unknown	1,000	192	0	0
	FADC	NA (NA, NA)	-0.59 (-0.68, 0.00)	0.05 (-0.08, 0.10)	0.01 (-0.07, 0.08)
	Unknown	1,000	200	30	0
	FADC (%)	NA (NA, NA)	-60 (-69, -8)	11 (-44, 21)	7 (-16, 19)
	Unknown	1,000	200	30	0

[1] Median (IQR); n (%)

11.6.3 Southern Africa (A-Z)

Table 26: Summary Statistics for Lesotho.

Group	Variable	2016 (N=840)	2017 (N=900)	2019 (N=970)
GWP	SWB (0-10)	4.0 (1.0, 5.0)	4.0 (1.0, 5.0)	4.0 (1.0, 5.0)
	Unknown	10	35	28
	Gender			
	Male	326 (39%)	376 (42%)	371 (38%)
	Female	514 (61%)	524 (58%)	599 (62%)
	Age	37 (24, 59)	35 (24, 57)	33 (23, 53)
	Income	483 (167, 1,393)	712 (296, 1,869)	666 (233, 1,631)
	Urbanicity			

(continued)

Group	Variable	2016 (N=840)	2017 (N=900)	2019 (N=970)
	Rural Area	600 (71%)	600 (67%)	499 (51%)
	Small Town	216 (26%)	279 (31%)	437 (45%)
	Large City	24 (2.9%)	21 (2.3%)	22 (2.3%)
	Suburb	0 (0%)	0 (0%)	12 (1.2%)
30 days	FC Before	NA (NA, NA)	5.2 (2.2, 7.8)	4.2 (1.1, 7.8)
	Unknown	840	0	0
	FC After	NA (NA, NA)	6.2 (2.9, 10.9)	2.6 (0.8, 4.6)
	Unknown	840	0	0
	FCC	NA (NA, NA)	0.67 (0.30, 0.90)	1.67 (0.50, 2.87)
	Unknown	840	0	0
	FCC (%)	NA (NA, NA)	14 (9, 18)	40 (34, 47)
	Unknown	840	0	0
	Mean FAD Before	NA (NA, NA)	775 (590, 1,018)	857 (621, 1,123)
	Unknown	840	0	0
	Mean FAD After	NA (NA, NA)	779 (539, 980)	990 (724, 1,204)
	Unknown	840	0	0
	FADC	NA (NA, NA)	-0.06 (-0.11, -0.02)	0.13 (0.10, 0.16)
	Unknown	840	0	0
	FADC (%)	NA (NA, NA)	-8 (-14, -2)	16 (11, 22)
	Unknown	840	0	0
90 days	FC Before	NA (NA, NA)	7 (4, 13)	5 (2, 10)
	Unknown	840	0	0
	FC After	NA (NA, NA)	11 (6, 19)	4 (2, 8)

(continued)

Group	Variable	2016 (N=840)	2017 (N=900)	2019 (N=970)
	Unknown	840	0	0
	FCC	NA (NA, NA)	0.49 (0.25, 0.96)	1.37 (0.49, 1.97)
	Unknown	840	0	0
	FCC (%)	NA (NA, NA)	8 (6, 14)	24 (19, 35)
	Unknown	840	20	0
	Mean FAD Before	NA (NA, NA)	771 (546, 941)	799 (554, 1,029)
	Unknown	840	0	0
	Mean FAD After	NA (NA, NA)	679 (445, 834)	861 (585, 1,079)
	Unknown	840	10	0
	FADC	NA (NA, NA)	-0.09 (-0.12, -0.06)	0.07 (0.04, 0.09)
	Unknown	840	10	0
	FADC (%)	NA (NA, NA)	-14 (-18, -10)	8 (5, 13)
	Unknown	840	10	0
180 days	FC Before	NA (NA, NA)	12 (7, 21)	8 (4, 16)
	Unknown	840	0	0
	FC After	NA (NA, NA)	14 (8, 24)	7 (4, 14)
	Unknown	840	0	0
	FCC	NA (NA, NA)	0.83 (0.58, 2.88)	1.71 (0.56, 2.75)
	Unknown	840	0	0
	FCC (%)	NA (NA, NA)	8 (5, 22)	21 (14, 28)
	Unknown	840	0	0
	Mean FAD Before	NA (NA, NA)	621 (419, 793)	700 (456, 916)
	Unknown	840	0	0

(continued)

Group	Variable	2016 (N=840)	2017 (N=900)	2019 (N=970)
	Mean FAD After	NA (NA, NA)	617 (399, 739)	780 (498, 1,006)
	Unknown	840	0	0
	FADC	NA (NA, NA)	-0.04 (-0.07, 0.01)	0.06 (0.04, 0.10)
	Unknown	840	0	0
	FADC (%)	NA (NA, NA)	-8 (-11, 1)	10 (5, 15)
	Unknown	840	0	0

[1] Median (IQR); n (%)

Table 27: Summary Statistics for Namibia.

Group	Variable	2017 (N=864)	2018 (N=878)	2019 (N=892)
GWP	SWB (0-10)	5.0 (3.0, 6.0)	5.0 (4.0, 6.0)	5.0 (3.0, 7.0)
	Unknown	12	9	7
	Gender			
	Male	277 (32%)	364 (41%)	403 (45%)
	Female	587 (68%)	514 (59%)	489 (55%)
	Age	28 (22, 37)	29 (23, 36)	29 (23, 38)
	Income	2,477 (849, 5,945)	2,878 (1,228, 7,369)	1,581 (641, 3,847)
	Urbanicity			
	Rural Area	234 (27%)	97 (11%)	176 (20%)
	Small Town	396 (46%)	390 (44%)	482 (54%)
	Large City	122 (14%)	24 (2.7%)	81 (9.1%)
	Suburb	112 (13%)	367 (42%)	153 (17%)
30 days	FC Before	7 (4, 44)	2 (0, 31)	0 (0, 3)

(continued)

Group	Variable	2017 (N=864)	2018 (N=878)	2019 (N=892)
	Unknown	342	0	0
	FC After	45 (11, 94)	2 (0, 14)	0 (0, 1)
	Unknown	342	0	0
	FCC	1 (0, 18)	1 (0, 14)	0 (0, 2)
	Unknown	342	0	0
	FCC (%)	14 (7, 45)	48 (27, 68)	77 (56, 95)
	Unknown	390	50	267
	Mean FAD Before	734 (343, 827)	899 (442, 1,352)	1,228 (959, 1,453)
	Unknown	390	36	202
	Mean FAD After	290 (195, 643)	971 (576, 1,293)	1,285 (1,209, 1,415)
	Unknown	354	28	313
	FADC	-0.31 (-0.49, 0.04)	0.08 (-0.03, 0.17)	0.28 (0.12, 0.43)
	Unknown	397	36	337
	FADC (%)	-62 (-67, 6)	8 (-8, 31)	28 (8, 56)
	Unknown	397	36	337
90 days	FC Before	31 (6, 107)	9 (1, 48)	1 (0, 10)
	FC After	41 (14, 106)	7 (1, 33)	0 (0, 1)
	FCC	14 (1, 29)	4 (0, 14)	1 (0, 8)
	FCC (%)	28 (9, 47)	38 (19, 53)	88 (52, 97)
	Unknown	24	16	85
	Mean FAD Before	361 (167, 791)	673 (316, 1,253)	1,118 (612, 1,354)
	Unknown	24	16	72
	Mean FAD After	311 (151, 622)	684 (320, 1,217)	1,253 (1,171, 1,441)

(continued)

Group	Variable	2017 (N=864)	2018 (N=878)	2019 (N=892)
	Unknown	8	3	192
	FADC	0.01 (-0.45, 0.14)	0.00 (-0.04, 0.08)	0.62 (0.15, 0.68)
	Unknown	24	24	192
	FADC (%)	5 (-65, 63)	0 (-11, 12)	86 (14, 120)
	Unknown	24	24	192
180 days	FC Before	94 (3, 165)	8 (1, 41)	3 (1, 21)
	FC After	39 (9, 126)	7 (1, 25)	1 (0, 2)
	FCC	24 (1, 71)	3 (0, 13)	2 (0, 19)
	FCC (%)	43 (13, 64)	31 (14, 48)	92 (62, 99)
	Unknown	24	12	10
	Mean FAD Before	132 (43, 907)	649 (353, 1,195)	885 (396, 1,250)
	Unknown	24	6	10
	Mean FAD After	363 (107, 742)	632 (354, 1,132)	1,193 (1,112, 1,423)
	Unknown	24	0	111
	FADC	0.03 (-0.03, 0.22)	-0.01 (-0.13, 0.09)	0.56 (0.19, 0.76)
	Unknown	24	6	111
	FADC (%)	14 (-4, 237)	-4 (-26, 12)	124 (26, 180)
	Unknown	24	6	111

[1] Median (IQR); n (%)

11.6.4 Western Afria (A-Z)

Table 28: Summary Statistics for Benin.

Group	Variable	2016 (N=704)	2017 (N=1000)	2018 (N=980)	2019 (N=1000)
GWP	SWB (0-10)	4.0 (2.0, 5.0)	5.0 (3.0, 7.0)	5.0 (3.5, 10.0)	5.0 (3.0, 8.0)
	Unknown	40	81	41	7
	Gender				
	Male	384 (55%)	544 (54%)	644 (66%)	591 (59%)
	Female	320 (45%)	456 (46%)	336 (34%)	409 (41%)
	Age	30 (23, 41)	28 (21, 40)	28 (22, 39)	27 (21, 37)
	Income	468 (211, 928)	593 (259, 1,297)	520 (208, 1,385)	528 (264, 1,319)
	Urbanicity				
	Rural Area	112 (16%)	352 (35%)	349 (36%)	324 (32%)
	Small Town	408 (58%)	424 (42%)	342 (35%)	485 (49%)
	Large City	144 (20%)	216 (22%)	97 (9.9%)	151 (15%)
	Suburb	40 (5.7%)	8 (0.8%)	192 (20%)	40 (4.0%)
30 days	FC Before	NA (NA, NA)	17 (2, 74)	1 (0, 16)	1 (0, 3)
	Unknown	704	421	605	240
	FC After	NA (NA, NA)	0.0 (0.0, 3.0)	1.6 (0.2, 6.7)	0.2 (0.0, 3.1)
	Unknown	704	421	605	240
	FCC	NA (NA, NA)	16 (2, 66)	1 (0, 16)	1 (0, 2)
	Unknown	704	421	605	240
	FCC (%)	NA (NA, NA)	100 (95, 100)	98 (94, 100)	100 (90, 100)
	Unknown	704	437	770	423
	Mean FAD Before	NA (NA, NA)	454 (141, 1,209)	676 (423, 1,010)	1,257 (1,088, 1,398)
	Unknown	704	421	770	363
	Mean FAD After	NA (NA, NA)	1,164 (777, 1,603)	1,172 (1,029, 1,259)	1,259 (1,098, 1,516)

(continued)

Group	Variable	2016 (N=704)	2017 (N=1000)	2018 (N=980)	2019 (N=1000)
	Unknown	704	592	639	429
	FADC	NA (NA, NA)	0.55 (0.46, 0.84)	0.39 (0.07, 0.84)	-0.20 (-0.44, 0.27)
	Unknown	704	592	814	573
	FADC (%)	NA (NA, NA)	137 (65, 427)	58 (7, 259)	-19 (-33, 21)
	Unknown	704	592	814	573
90 days	FC Before	NA (NA, NA)	13 (2, 30)	2 (0, 14)	7 (2, 25)
	Unknown	704	0	92	34
	FC After	NA (NA, NA)	5 (1, 20)	13 (2, 33)	9 (3, 33)
	Unknown	704	0	92	34
	FCC	NA (NA, NA)	7 (1, 22)	2 (0, 7)	4 (1, 14)
	Unknown	704	0	92	34
	FCC (%)	NA (NA, NA)	73 (46, 95)	71 (42, 91)	78 (44, 98)
	Unknown	704	0	216	34
	Mean FAD Before	NA (NA, NA)	651 (358, 1,138)	1,019 (466, 1,387)	988 (611, 1,174)
	Unknown	704	0	186	34
	Mean FAD After	NA (NA, NA)	924 (447, 1,205)	786 (304, 1,086)	869 (441, 1,086)
	Unknown	704	35	92	54
	FADC	NA (NA, NA)	0.14 (-0.09, 0.44)	-0.15 (-0.49, 0.01)	-0.24 (-0.47, 0.30)
	Unknown	704	35	186	54
	FADC (%)	NA (NA, NA)	29 (-13, 77)	-18 (-42, 3)	-24 (-51, 37)
	Unknown	704	35	186	54
180 days	FC Before	NA (NA, NA)	27 (6, 75)	5 (1, 21)	16 (5, 29)
	Unknown	704	0	0	0

(continued)

Group	Variable	2016 (N=704)	2017 (N=1000)	2018 (N=980)	2019 (N=1000)
	FC After	NA (NA, NA)	46 (12, 98)	18 (8, 37)	32 (9, 70)
	Unknown	704	0	0	0
	FCC	NA (NA, NA)	4 (1, 9)	2 (0, 6)	5 (2, 8)
	Unknown	704	0	0	0
	FCC (%)	NA (NA, NA)	19 (11, 31)	48 (12, 68)	41 (30, 50)
	Unknown	704	0	0	10
	Mean FAD Before	NA (NA, NA)	350 (150, 796)	890 (475, 1,181)	617 (399, 957)
	Unknown	704	0	0	0
	Mean FAD After	NA (NA, NA)	260 (122, 678)	503 (345, 779)	408 (168, 766)
	Unknown	704	0	0	4
	FADC	NA (NA, NA)	-0.06 (-0.17, -0.02)	-0.28 (-0.51, -0.05)	-0.09 (-0.33, 0.00)
	Unknown	704	0	0	4
	FADC (%)	NA (NA, NA)	-21 (-38, -7)	-37 (-58, -9)	-23 (-51, 0)
	Unknown	704	0	0	4

[1] Median (IQR); n (%)

Table 29: Summary Statistics for Burkina Faso.

Group	Variable	2016 (N=24)	2017 (N=1000)	2018 (N=1000)	2019 (N=1000)
GWP	SWB (0-10)	4.00 (3.75, 5.00)	5.00 (3.00, 6.00)	5.00 (3.00, 6.00)	5.00 (3.00, 6.00)
	Unknown	4	31	66	80
	Gender				
	Male	9 (38%)	659 (66%)	625 (63%)	606 (61%)
	Female	15 (63%)	341 (34%)	375 (38%)	394 (39%)

(continued)

Group	Variable	2016 (N=24)	2017 (N=1000)	2018 (N=1000)	2019 (N=1000)
	Age	27 (19, 37)	29 (22, 39)	30 (22, 40)	30 (23, 40)
	Income	223 (99, 546)	883 (331, 2,004)	664 (228, 1,860)	534 (223, 1,335)
	Urbanicity				
	Rural Area	8 (33%)	344 (34%)	360 (36%)	254 (25%)
	Small Town	8 (33%)	416 (42%)	440 (44%)	559 (56%)
	Large City	8 (33%)	224 (22%)	190 (19%)	175 (18%)
	Suburb	0 (0%)	16 (1.6%)	10 (1.0%)	12 (1.2%)
30 days	FC Before	NA (NA, NA)	1 (0, 2)	4 (2, 4)	1 (0, 6)
	Unknown	24	64	39	13
	FC After	NA (NA, NA)	0 (0, 0)	1 (0, 1)	1 (0, 6)
	Unknown	24	64	39	13
	FCC	NA (NA, NA)	1 (0, 2)	4 (2, 4)	1 (0, 5)
	Unknown	24	64	39	13
	FCC (%)	NA (NA, NA)	97 (87, 100)	87 (85, 92)	88 (68, 100)
	Unknown	24	245	99	94
	Mean FAD Before	NA (NA, NA)	1,293 (917, 1,379)	700 (700, 1,073)	1,172 (759, 1,328)
	Unknown	24	229	99	89
	Mean FAD After	NA (NA, NA)	1,333 (1,263, 1,504)	1,185 (1,095, 1,296)	1,012 (740, 1,272)
	Unknown	24	409	169	99
	FADC	NA (NA, NA)	0.35 (0.18, 0.65)	0.49 (0.39, 0.58)	-0.13 (-0.48, 0.13)
	Unknown	24	417	219	182
	FADC (%)	NA (NA, NA)	31 (13, 80)	69 (40, 76)	-11 (-45, 16)
	Unknown	24	417	219	182

(continued)

Group	Variable	2016 (N=24)	2017 (N=1000)	2018 (N=1000)	2019 (N=1000)
90 days	FC Before	NA (NA, NA)	0 (0, 2)	1 (0, 2)	2 (0, 7)
	Unknown	24	0	0	0
	FC After	NA (NA, NA)	0 (0, 1)	0 (0, 0)	2 (0, 6)
	Unknown	24	0	0	0
	FCC	NA (NA, NA)	0.2 (0.0, 1.3)	0.4 (0.1, 0.9)	0.3 (0.0, 2.5)
	Unknown	24	0	0	0
	FCC (%)	NA (NA, NA)	66 (57, 85)	75 (34, 77)	34 (21, 60)
	Unknown	24	128	90	50
	Mean FAD Before	NA (NA, NA)	1,323 (1,162, 1,466)	1,200 (1,073, 1,325)	1,173 (705, 1,336)
	Unknown	24	96	70	30
	Mean FAD After	NA (NA, NA)	1,372 (1,292, 1,484)	1,306 (1,299, 1,310)	1,110 (763, 1,279)
	Unknown	24	144	80	10
	FADC	NA (NA, NA)	0.15 (0.02, 0.26)	0.19 (-0.09, 0.20)	-0.07 (-0.20, 0.07)
	Unknown	24	152	110	40
	FADC (%)	NA (NA, NA)	12 (1, 29)	16 (-8, 17)	-9 (-21, 7)
	Unknown	24	152	110	40
180 days	FC Before	NA (NA, NA)	2.1 (0.3, 3.9)	0.2 (0.2, 1.0)	0.4 (0.1, 2.1)
	Unknown	24	0	0	0
	FC After	NA (NA, NA)	1.8 (0.5, 3.6)	0.3 (0.3, 1.0)	0.4 (0.0, 1.7)
	Unknown	24	0	0	0
	FCC	NA (NA, NA)	0.61 (0.06, 1.27)	0.03 (0.02, 0.40)	0.13 (0.03, 0.87)
	Unknown	24	0	0	0
	FCC (%)	NA (NA, NA)	23 (14, 39)	13 (10, 25)	33 (21, 59)

(continued)

Group	Variable	2016 (N=24)	2017 (N=1000)	2018 (N=1000)	2019 (N=1000)
	Unknown	24	40	40	80
	Mean FAD Before	NA (NA, NA)	1,124 (842, 1,318)	1,360 (1,237, 1,367)	1,294 (1,107, 1,426)
	Unknown	24	32	30	50
	Mean FAD After	NA (NA, NA)	1,144 (887, 1,277)	1,335 (1,221, 1,337)	1,315 (1,201, 1,448)
	Unknown	24	32	30	73
	FADC	NA (NA, NA)	-0.02 (-0.11, 0.09)	-0.05 (-0.14, 0.00)	0.07 (0.00, 0.13)
	Unknown	24	40	40	90
	FADC (%)	NA (NA, NA)	-2 (-11, 10)	-4 (-11, 0)	6 (0, 11)
	Unknown	24	40	40	90

[1] Median (IQR); n (%)

Table 30: Summary Statistics for Ghana.

Group	Variable	2016 (N=264)	2017 (N=464)	2018 (N=770)	2019 (N=969)
GWP	SWB (0-10)	5.00 (3.00, 7.00)	5.00 (4.00, 7.00)	5.00 (3.00, 7.00)	5.00 (4.00, 6.00)
	Unknown	3	24	10	8
	Gender				
	Male	137 (52%)	246 (53%)	436 (57%)	580 (60%)
	Female	127 (48%)	218 (47%)	334 (43%)	389 (40%)
	Age	29 (23, 40)	28 (22, 38)	29 (24, 37)	28 (22, 35)
	Income	854 (342, 1,708)	1,101 (480, 2,563)	1,623 (747, 3,652)	1,376 (550, 3,096)
	Urbanicity				
	Rural Area	166 (63%)	114 (25%)	90 (12%)	86 (8.9%)
	Small Town	28 (11%)	174 (38%)	140 (18%)	539 (56%)

(continued)

Group	Variable	2016 (N=264)	2017 (N=464)	2018 (N=770)	2019 (N=969)
	Large City	18 (6.8%)	72 (16%)	109 (14%)	116 (12%)
	Suburb	52 (20%)	104 (22%)	431 (56%)	228 (24%)
30 days	FC Before	NA (NA, NA)	5 (1, 36)	58 (4, 107)	33 (6, 92)
	Unknown	264	264	30	0
	FC After	NA (NA, NA)	3 (0, 11)	21 (3, 131)	39 (7, 91)
	Unknown	264	264	30	0
	FCC	NA (NA, NA)	5 (1, 22)	16 (2, 58)	10 (3, 32)
	Unknown	264	264	30	0
	FCC (%)	NA (NA, NA)	97 (81, 99)	61 (38, 90)	48 (27, 83)
	Unknown	264	272	46	0
	Mean FAD Before	NA (NA, NA)	878 (601, 1,235)	586 (139, 1,122)	686 (345, 1,026)
	Unknown	264	272	41	0
	Mean FAD After	NA (NA, NA)	1,133 (967, 1,248)	805 (143, 1,085)	598 (271, 1,012)
	Unknown	264	276	40	0
	FADC	NA (NA, NA)	0.10 (-0.04, 0.67)	-0.01 (-0.28, 0.16)	-0.08 (-0.25, 0.05)
	Unknown	264	284	51	0
	FADC (%)	NA (NA, NA)	11 (-3, 89)	-6 (-39, 61)	-14 (-41, 15)
	Unknown	264	284	51	0
90 days	FC Before	NA (NA, NA)	14 (2, 53)	67 (7, 111)	40 (8, 137)
	Unknown	264	8	17	0
	FC After	NA (NA, NA)	11 (2, 60)	28 (7, 131)	61 (17, 121)
	Unknown	264	8	17	0
	FCC	NA (NA, NA)	5 (1, 14)	22 (2, 56)	14 (4, 34)

(continued)

Group	Variable	2016 (N=264)	2017 (N=464)	2018 (N=770)	2019 (N=969)
	Unknown	264	8	17	0
	FCC (%)	NA (NA, NA)	59 (36, 83)	55 (37, 76)	39 (22, 65)
	Unknown	264	8	33	0
	Mean FAD Before	NA (NA, NA)	819 (488, 1,222)	463 (106, 1,005)	539 (99, 912)
	Unknown	264	8	28	0
	Mean FAD After	NA (NA, NA)	738 (477, 1,136)	535 (129, 1,035)	452 (159, 697)
	Unknown	264	8	17	0
	FADC	NA (NA, NA)	-0.05 (-0.26, 0.20)	0.00 (-0.14, 0.19)	-0.08 (-0.33, 0.01)
	Unknown	264	8	28	0
	FADC (%)	NA (NA, NA)	-8 (-32, 28)	-1 (-31, 60)	-26 (-50, 5)
	Unknown	264	8	28	0
180 days	FC Before	NA (NA, NA)	42 (4, 175)	75 (14, 164)	52 (12, 136)
	Unknown	264	0	0	0
	FC After	NA (NA, NA)	51 (12, 171)	39 (9, 138)	64 (20, 134)
	Unknown	264	0	0	0
	FCC	NA (NA, NA)	5 (0, 21)	27 (6, 49)	14 (4, 36)
	Unknown	264	0	0	0
	FCC (%)	NA (NA, NA)	10 (3, 22)	57 (33, 79)	37 (21, 62)
	Unknown	264	0	0	0
	Mean FAD Before	NA (NA, NA)	448 (85, 1,232)	351 (70, 920)	499 (133, 806)
	Unknown	264	0	0	0
	Mean FAD After	NA (NA, NA)	394 (102, 721)	399 (107, 932)	430 (135, 659)
	Unknown	264	0	0	0

(continued)

Group	Variable	2016 (N=264)	2017 (N=464)	2018 (N=770)	2019 (N=969)
	FADC	NA (NA, NA)	-0.13 (-0.47, 0.01)	0.01 (-0.08, 0.14)	-0.07 (-0.24, 0.01)
	Unknown	264	0	0	0
	FADC (%)	NA (NA, NA)	-29 (-52, 9)	6 (-24, 49)	-16 (-46, 10)
	Unknown	264	0	0	0

[1] Median (IQR); n (%)

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Group	Variable	2017 (N=976)	2018 (N=930)
GWP	SWB (0-10)	5.00 (3.00, 7.00)	5.00 (3.00, 7.00)
	Unknown	42	55
	Gender		
	Male	663 (68%)	658 (71%)
	Female	313 (32%)	272 (29%)
	Age	30 (23, 41)	30 (22, 40)
	Income	1,203 (501, 2,506)	1,316 (548, 2,715)
	Urbanicity		
	Rural Area	144 (15%)	170 (18%)
	Small Town	560 (57%)	390 (42%)
	Large City	192 (20%)	320 (34%)
	Suburb	80 (8.2%)	50 (5.4%)
30 days	FC Before	9 (3, 18)	24 (0, 77)
	Unknown	261	627

(continued)

Group	Variable	2017 (N=976)	2018 (N=930)
	FC After	5 (0, 20)	1 (0, 22)
	Unknown	261	627
	FCC	6 (3, 13)	24 (0, 65)
	Unknown	261	627
	FCC (%)	95 (83, 100)	100 (89, 100)
	Unknown	302	680
	Mean FAD Before	1,041 (832, 1,209)	797 (119, 1,377)
	Unknown	285	647
	Mean FAD After	1,025 (868, 1,395)	1,067 (517, 1,361)
	Unknown	311	680
	FADC	0.21 (-0.19, 0.39)	0.38 (0.12, 0.87)
	Unknown	361	710
	FADC (%)	18 (-18, 43)	97 (14, 748)
	Unknown	361	710
90 days	FC Before	12 (4, 33)	5 (1, 24)
	Unknown	40	244
	FC After	46 (8, 104)	5 (1, 22)
	Unknown	40	244
	FCC	5 (2, 13)	3 (0, 23)
	Unknown	40	244
	FCC (%)	50 (25, 72)	83 (58, 99)
	Unknown	72	368
	Mean FAD Before	1,011 (531, 1,180)	976 (574, 1,262)

(continued)

Group	Variable	2017 (N=976)	2018 (N=930)
	Unknown	72	348
	Mean FAD After	670 (139, 1,064)	1,069 (792, 1,264)
	Unknown	48	294
	FADC	-0.07 (-0.48, 0.03)	0.11 (-0.20, 0.28)
	Unknown	72	384
	FADC (%)	-17 (-65, 10)	12 (-21, 60)
	Unknown	72	384
180 days	FC Before	188 (60, 251)	13 (4, 54)
	Unknown	0	110
	FC After	101 (25, 225)	60 (11, 127)
	Unknown	0	110
	FCC	19 (6, 73)	5 (1, 18)
	Unknown	0	110
	FCC (%)	17 (5, 71)	35 (26, 59)
	Unknown	0	200
	Mean FAD Before	40 (16, 391)	823 (242, 1,154)
	Unknown	0	178
	Mean FAD After	145 (24, 889)	362 (134, 980)
	Unknown	0	130
	FADC	0.00 (-0.01, 0.26)	-0.30 (-0.59, 0.00)
	Unknown	0	210
	FADC (%)	12 (-18, 105)	-37 (-73, -3)

(continued)

Group	Variable	2017 (N=976)	2018 (N=930)
	Unknown	0	210

[1] Median (IQR); n (%)

::: :::

Table 31: Summary Statistics for Liberia.

Group	Variable	2017 (N=848)	2018 (N=530)	2019 (N=930)
GWP	SWB (0-10)	4.0 (1.0, 6.3)	3.0 (1.0, 6.0)	5.0 (1.0, 10.0)
	Unknown	16	10	25
	Gender			
	Male	340 (40%)	237 (45%)	365 (39%)
	Female	508 (60%)	293 (55%)	565 (61%)
	Age	31 (20, 43)	31 (21, 42)	30 (21, 40)
	Income	334 (149, 694)	318 (128, 639)	260 (97, 585)
	Urbanicity			
	Rural Area	97 (11%)	75 (14%)	64 (6.9%)
	Small Town	451 (53%)	253 (48%)	421 (45%)
	Large City	87 (10%)	72 (14%)	163 (18%)
	Suburb	213 (25%)	130 (25%)	282 (30%)
30 days	FC Before	2 (0, 9)	2 (0, 6)	2 (0, 8)
	Unknown	660	50	170
	FC After	2 (0, 15)	6 (0, 9)	19 (5, 47)
	Unknown	660	50	170

(continued)

Group	Variable	2017 (N=848)	2018 (N=530)	2019 (N=930)
	FCC	2 (0, 8)	1 (0, 6)	1 (0, 2)
	Unknown	660	50	170
	FCC (%)	100 (85, 100)	100 (95, 100)	45 (22, 93)
	Unknown	712	80	300
	Mean FAD Before	1,153 (1,077, 1,308)	1,290 (1,173, 1,385)	1,176 (1,023, 1,372)
	Unknown	704	70	240
	Mean FAD After	1,259 (1,030, 1,419)	1,051 (1,006, 1,331)	815 (704, 1,023)
	Unknown	676	120	240
	FADC	0.04 (-0.49, 0.16)	-0.08 (-0.39, 0.18)	-0.28 (-0.74, -0.13)
	Unknown	736	140	290
	FADC (%)	3 (-38, 13)	-6 (-30, 15)	-28 (-60, -11)
	Unknown	736	140	290
90 days	FC Before	128 (35, 247)	10 (2, 51)	136 (38, 254)
	FC After	11 (3, 47)	149 (31, 262)	174 (30, 247)
	FCC	47 (21, 219)	3 (1, 8)	22 (10, 42)
	FCC (%)	91 (70, 97)	28 (8, 42)	21 (10, 51)
	Unknown	0	0	10
	Mean FAD Before	366 (26, 740)	1,108 (631, 1,182)	285 (19, 660)
	Unknown	0	0	10
	Mean FAD After	1,013 (652, 1,188)	184 (15, 648)	208 (26, 623)
	FADC	0.58 (0.09, 0.94)	-0.59 (-0.91, -0.17)	-0.01 (-0.10, 0.03)
	Unknown	0	0	10
	FADC (%)	84 (14, 1,980)	-75 (-95, -51)	-4 (-43, 43)

(continued)

Group	Variable	2017 (N=848)	2018 (N=530)	2019 (N=930)
	Unknown	0	0	10
180 days	FC Before	275 (104, 298)	111 (38, 284)	283 (122, 299)
	FC After	242 (53, 295)	285 (155, 300)	280 (94, 298)
	FCC	8 (4, 24)	4 (1, 8)	5 (3, 8)
	FCC (%)	7 (2, 30)	2 (1, 4)	3 (1, 6)
	Mean FAD Before	7 (1, 373)	321 (4, 677)	5 (1, 335)
	Mean FAD After	64 (2, 529)	5 (1, 289)	7 (2, 332)
	FADC	0.00 (-0.03, 0.04)	0.00 (-0.54, 0.00)	0.00 (-0.02, 0.00)
	FADC (%)	-13 (-27, 71)	-9 (-99, 18)	-8 (-16, 7)

[1] Median (IQR); n (%)

Table 32: Summary Statistics for Mali.

Group	Variable	2017 (N=896)	2018 (N=890)	2019 (N=1010)
GWP	SWB (0-10)	5.0 (3.0, 6.0)	4.0 (3.0, 5.0)	5.0 (3.0, 7.0)
	Unknown	47	43	23
	Gender			
	Male	469 (52%)	537 (60%)	548 (54%)
	Female	427 (48%)	353 (40%)	462 (46%)
	Age	31 (23, 45)	32 (23, 43)	32 (24, 43)
	Income	525 (262, 1,049)	636 (279, 1,325)	523 (231, 1,307)
	Urbanicity			
	Rural Area	152 (17%)	220 (25%)	145 (14%)
	Small Town	512 (57%)	430 (48%)	595 (59%)

(continued)

Group	Variable	2017 (N=896)	2018 (N=890)	2019 (N=1010)
	Large City	232 (26%)	240 (27%)	240 (24%)
	Suburb	0 (0%)	0 (0%)	30 (3.0%)
30 days	FC Before	4 (1, 16)	0 (0, 0)	4 (0, 23)
	Unknown	56	50	43
	FC After	14 (1, 33)	1 (0, 2)	4 (1, 19)
	Unknown	56	50	43
	FCC	2 (0, 7)	0 (0, 0)	3 (0, 16)
	Unknown	56	50	43
	FCC (%)	58 (36, 95)	4 (0, 34)	88 (63, 99)
	Unknown	106	322	53
	Mean FAD Before	993 (642, 1,194)	1,344 (1,191, 1,455)	890 (430, 1,298)
	Unknown	82	290	53
	Mean FAD After	632 (291, 1,091)	1,219 (1,054, 1,377)	935 (553, 1,174)
	Unknown	75	130	62
	FADC	-0.20 (-0.53, 0.00)	-0.49 (-0.72, -0.26)	-0.05 (-0.30, 0.18)
	Unknown	101	312	82
	FADC (%)	-26 (-55, 1)	-39 (-48, -22)	-4 (-32, 34)
	Unknown	101	312	82
90 days	FC Before	1 (0, 6)	0 (0, 2)	2 (1, 15)
	FC After	1 (0, 15)	2 (0, 4)	5 (2, 19)
	FCC	0.3 (0.0, 2.0)	0.0 (0.0, 0.2)	0.9 (0.0, 6.2)
	FCC (%)	36 (19, 54)	9 (1, 27)	34 (15, 60)
	Unknown	119	140	58

(continued)

Group	Variable	2017 (N=896)	2018 (N=890)	2019 (N=1010)
	Mean FAD Before	1,105 (605, 1,323)	1,253 (1,053, 1,374)	1,007 (470, 1,181)
	Unknown	88	130	53
	Mean FAD After	1,086 (370, 1,341)	1,108 (903, 1,335)	835 (467, 1,079)
	Unknown	82	90	18
	FADC	-0.08 (-0.20, 0.04)	-0.19 (-0.39, -0.01)	-0.12 (-0.38, 0.04)
	Unknown	125	168	68
	FADC (%)	-6 (-37, 5)	-19 (-31, -2)	-21 (-35, 7)
	Unknown	125	168	68
180 days	FC Before	2 (0, 6)	7 (2, 26)	1 (0, 5)
	FC After	1 (0, 5)	3 (1, 9)	1 (0, 3)
	FCC	1 (0, 2)	4 (1, 21)	0 (0, 1)
	FCC (%)	47 (33, 67)	61 (45, 79)	32 (19, 55)
	Unknown	96	10	148
	Mean FAD Before	1,096 (702, 1,310)	814 (299, 1,060)	1,168 (708, 1,367)
	Unknown	72	10	118
	Mean FAD After	1,174 (755, 1,394)	1,031 (824, 1,239)	1,136 (754, 1,376)
	Unknown	86	10	100
	FADC	0.13 (0.02, 0.28)	0.22 (0.16, 0.44)	0.07 (-0.06, 0.13)
	Unknown	102	10	140
	FADC (%)	16 (2, 26)	36 (22, 101)	7 (-8, 14)
	Unknown	102	10	140

[1] Median (IQR); n (%)

Table 33: Summary Statistics for Mauritania.

Group	Variable	2017 (N=1000)	2018 (N=930)	2019 (N=1100)
GWP	SWB (0-10)	5.00 (4.00, 6.00)	5.00 (3.00, 6.00)	4.00 (3.00, 5.00)
	Unknown	23	55	24
	Gender			
	Male	612 (61%)	522 (56%)	581 (53%)
	Female	388 (39%)	408 (44%)	519 (47%)
	Age	30 (22, 39)	33 (26, 40)	30 (22, 39)
	Income	NA (NA, NA)	NA (NA, NA)	1,419 (506, 2,380)
	Unknown	1,000	930	0
	Urbanicity			
	Rural Area	208 (21%)	420 (45%)	60 (5.5%)
	Small Town	376 (38%)	200 (22%)	557 (51%)
	Large City	392 (39%)	250 (27%)	333 (30%)
	Suburb	24 (2.4%)	60 (6.5%)	150 (14%)
30 days	FC Before	0.00 (0.00, 0.05)	0.05 (0.00, 0.55)	0.02 (0.01, 0.66)
	Unknown	8	1	0
	FC After	0.01 (0.00, 0.02)	0.00 (0.00, 1.15)	0.09 (0.06, 1.11)
	Unknown	8	1	0
	FCC	0.00 (0.00, 0.03)	0.03 (0.00, 0.25)	0.01 (0.01, 0.22)
	Unknown	8	1	0
	FCC (%)	59 (26, 100)	51 (30, 87)	49 (24, 92)
	Unknown	618	421	235
	Mean FAD Before	1,369 (1,189, 1,452)	1,309 (1,203, 1,405)	1,400 (1,173, 1,522)
	Unknown	618	401	205

(continued)

Group	Variable	2017 (N=1000)	2018 (N=930)	2019 (N=1100)
	Mean FAD After	1,521 (1,468, 1,521)	1,228 (994, 1,402)	1,370 (1,180, 1,480)
	Unknown	312	406	140
	FADC	0.09 (0.05, 0.24)	-0.16 (-0.43, 0.02)	-0.16 (-0.18, -0.01)
	Unknown	680	446	225
	FADC (%)	6 (4, 20)	-17 (-33, 1)	-10 (-15, -1)
	Unknown	680	446	225
90 days	FC Before	0.01 (0.01, 0.08)	0.00 (0.00, 0.04)	0.01 (0.00, 0.69)
	FC After	0.02 (0.00, 0.08)	0.00 (0.00, 0.03)	0.01 (0.00, 0.84)
	FCC	0.01 (0.00, 0.04)	0.00 (0.00, 0.03)	0.01 (0.00, 0.33)
	FCC (%)	81 (27, 81)	93 (53, 100)	60 (29, 100)
	Unknown	246	460	270
	Mean FAD Before	1,445 (1,352, 1,520)	1,411 (1,327, 1,500)	1,373 (1,185, 1,519)
	Unknown	246	450	250
	Mean FAD After	1,488 (1,347, 1,488)	1,398 (1,276, 1,493)	1,300 (1,000, 1,387)
	Unknown	280	580	489
	FADC	-0.12 (-0.14, 0.01)	-0.06 (-0.20, 0.17)	-0.03 (-0.11, 0.13)
	Unknown	318	590	549
	FADC (%)	-9 (-9, 1)	-4 (-14, 14)	-2 (-8, 11)
	Unknown	318	590	549
180 days	FC Before	0.01 (0.01, 0.09)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
	FC After	0.01 (0.00, 0.43)	0.00 (0.00, 0.00)	0.00 (0.00, 0.01)
	FCC	0.01 (0.00, 0.01)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
	FCC (%)	71 (10, 100)	100 (64, 100)	36 (12, 54)

(continued)

Group	Variable	2017 (N=1000)	2018 (N=930)	2019 (N=1100)
	Unknown	221	744	840
	Mean FAD Before	1,481 (1,350, 1,517)	1,400 (1,329, 1,429)	1,392 (1,309, 1,504)
	Unknown	221	734	830
	Mean FAD After	1,377 (1,184, 1,519)	1,365 (1,272, 1,416)	1,413 (1,220, 1,501)
	Unknown	391	810	765
	FADC	-0.07 (-0.18, 0.01)	0.11 (0.11, 0.26)	-0.11 (-0.27, -0.05)
	Unknown	476	830	877
	FADC (%)	-6 (-13, 1)	8 (8, 23)	-9 (-17, -4)
	Unknown	476	830	877

[1] Median (IQR); n (%)

Table 34: Summary Statistics for Niger.

Group	Variable	2016 (N=976)	2017 (N=960)	2018 (N=720)	2019 (N=760)
GWP	SWB (0-10)	4.0 (3.0, 5.0)	5.0 (3.0, 6.0)	5.0 (2.0, 9.0)	5.0 (3.0, 7.0)
	Unknown	14	43	197	38
	Gender				
	Male	522 (53%)	538 (56%)	391 (54%)	409 (54%)
	Female	454 (47%)	422 (44%)	329 (46%)	351 (46%)
	Age	28 (20, 40)	30 (21, 41)	31 (21, 47)	33 (24, 45)
	Income	406 (181, 774)	303 (88, 884)	NA (NA, NA)	426 (204, 851)
	Unknown	0	0	720	0
	Urbanicity				
	Rural Area	368 (38%)	504 (53%)	152 (21%)	271 (36%)

(continued)

Group	Variable	2016 (N=976)	2017 (N=960)	2018 (N=720)	2019 (N=760)
	Small Town	496 (51%)	336 (35%)	456 (63%)	419 (55%)
	Large City	80 (8.2%)	96 (10%)	112 (16%)	60 (7.9%)
	Suburb	32 (3.3%)	24 (2.5%)	0 (0%)	10 (1.3%)
30 days	FC Before	NA (NA, NA)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	1.51 (0.25, 3.58)
	Unknown	976	21	20	0
	FC After	NA (NA, NA)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.76 (0.25, 3.29)
	Unknown	976	21	20	0
	FCC	NA (NA, NA)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	1.03 (0.11, 2.58)
	Unknown	976	21	20	0
	FCC (%)	NA (NA, NA)	100 (99, 100)	100 (78, 100)	65 (41, 82)
	Unknown	976	834	603	30
	Mean FAD Before	NA (NA, NA)	1,347 (1,269, 1,540)	1,390 (1,312, 1,508)	1,050 (848, 1,292)
	Unknown	976	802	583	30
	Mean FAD After	NA (NA, NA)	1,274 (1,269, 1,457)	1,450 (1,348, 1,520)	1,187 (955, 1,301)
	Unknown	976	882	593	57
	FADC	NA (NA, NA)	0.26 (0.24, 0.31)	0.01 (-0.18, 0.35)	0.06 (-0.06, 0.34)
	Unknown	976	882	670	73
	FADC (%)	NA (NA, NA)	20 (19, 21)	1 (-14, 40)	5 (-14, 36)
	Unknown	976	882	670	73
90 days	FC Before	NA (NA, NA)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.75 (0.13, 2.11)
	Unknown	976	0	0	0
	FC After	NA (NA, NA)	0.00 (0.00, 0.01)	0.00 (0.00, 0.00)	0.29 (0.04, 0.98)
	Unknown	976	0	0	0

(continued)

Group	Variable	2016 (N=976)	2017 (N=960)	2018 (N=720)	2019 (N=760)
	FCC	NA (NA, NA)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.37 (0.05, 1.39)
	Unknown	976	0	0	0
	FCC (%)	NA (NA, NA)	88 (50, 93)	96 (94, 98)	72 (39, 91)
	Unknown	976	756	700	40
	Mean FAD Before	NA (NA, NA)	1,459 (1,396, 1,535)	1,185 (740, 1,847)	1,209 (992, 1,365)
	Unknown	976	710	690	30
	Mean FAD After	NA (NA, NA)	1,511 (1,434, 1,521)	1,515 (1,447, 1,525)	1,282 (1,137, 1,411)
	Unknown	976	685	598	110
	FADC	NA (NA, NA)	0.12 (0.00, 0.18)	0.63 (0.35, 0.72)	0.15 (-0.01, 0.41)
	Unknown	976	764	691	120
	FADC (%)	NA (NA, NA)	8 (0, 12)	61 (19, 85)	14 (-2, 37)
	Unknown	976	764	691	120
180 days	FC Before	NA (NA, NA)	0.00 (0.00, 0.12)	0.00 (0.00, 0.00)	0.03 (0.00, 0.17)
	Unknown	976	0	0	0
	FC After	NA (NA, NA)	0.01 (0.00, 0.10)	0.00 (0.00, 0.00)	0.01 (0.00, 0.12)
	Unknown	976	0	0	0
	FCC	NA (NA, NA)	0.00 (0.00, 0.03)	0.00 (0.00, 0.00)	0.01 (0.00, 0.08)
	Unknown	976	0	0	0
	FCC (%)	NA (NA, NA)	49 (14, 72)	38 (12, 66)	49 (22, 100)
	Unknown	976	520	630	239
	Mean FAD Before	NA (NA, NA)	1,394 (1,322, 1,480)	1,463 (1,358, 1,673)	1,446 (1,327, 1,511)
	Unknown	976	472	590	203
	Mean FAD After	NA (NA, NA)	1,433 (1,305, 1,483)	1,469 (1,377, 1,587)	1,434 (1,350, 1,516)

(continued)

Group	Variable	2016 (N=976)	2017 (N=960)	2018 (N=720)	2019 (N=760)
	Unknown	976	416	480	310
	FADC	NA (NA, NA)	0.00 (-0.04, 0.10)	0.00 (-0.02, 0.10)	-0.02 (-0.11, 0.05)
	Unknown	976	520	600	360
	FADC (%)	NA (NA, NA)	0 (-3, 7)	0 (-1, 6)	-1 (-12, 4)
	Unknown	976	520	600	360

[1] Median (IQR); n (%)

Table 35: Summary Statistics for Nigeria.

Group	Variable	2016 (N=808)	2017 (N=808)	2018 (N=890)	2019 (N=2960)
GWP	SWB (0-10)	5.0 (4.0, 7.0)	5.0 (4.0, 8.0)	5.0 (4.0, 7.0)	4.0 (2.0, 6.0)
	Unknown	24	26	39	72
	Gender				
	Male	428 (53%)	463 (57%)	535 (60%)	1,676 (57%)
	Female	380 (47%)	345 (43%)	355 (40%)	1,284 (43%)
	Age	28 (22, 36)	28 (22, 39)	30 (24, 38)	29 (23, 38)
	Income	905 (402, 2,113)	1,190 (547, 2,736)	1,341 (657, 2,346)	812 (369, 1,723)
	Urbanicity				
	Rural Area	179 (22%)	278 (34%)	162 (18%)	840 (28%)
	Small Town	408 (50%)	319 (39%)	401 (45%)	1,372 (46%)
	Large City	139 (17%)	114 (14%)	181 (20%)	504 (17%)
	Suburb	82 (10%)	97 (12%)	146 (16%)	244 (8.2%)
30 days	FC Before	NA (NA, NA)	0 (0, 1)	0 (0, 2)	9 (1, 34)
	Unknown	808	248	502	1,614

(continued)

Group	Variable	2016 (N=808)	2017 (N=808)	2018 (N=890)	2019 (N=2960)
	FC After	NA (NA, NA)	0 (0, 38)	0 (0, 1)	4 (0, 20)
	Unknown	808	248	502	1,614
	FCC	NA (NA, NA)	0 (0, 1)	0 (0, 2)	5 (1, 24)
	Unknown	808	248	502	1,614
	FCC (%)	NA (NA, NA)	70 (35, 95)	100 (95, 100)	91 (71, 100)
	Unknown	808	547	574	1,761
	Mean FAD Before	NA (NA, NA)	1,248 (1,052, 1,385)	1,317 (1,121, 1,442)	748 (410, 1,182)
	Unknown	808	534	564	1,741
	Mean FAD After	NA (NA, NA)	884 (465, 1,411)	1,224 (994, 1,464)	862 (492, 1,241)
	Unknown	808	392	713	1,798
	FADC	NA (NA, NA)	-0.51 (-0.94, -0.07)	0.16 (-0.12, 0.86)	0.09 (-0.18, 0.36)
	Unknown	808	550	725	1,908
	FADC (%)	NA (NA, NA)	-51 (-75, -23)	11 (-11, 66)	21 (-17, 88)
	Unknown	808	550	725	1,908
90 days	FC Before	NA (NA, NA)	43 (0, 148)	2 (0, 38)	9 (1, 32)
	Unknown	808	0	0	1,204
	FC After	NA (NA, NA)	15 (0, 99)	3 (0, 18)	3 (0, 20)
	Unknown	808	0	0	1,204
	FCC	NA (NA, NA)	15 (0, 45)	1 (0, 24)	6 (1, 21)
	Unknown	808	0	0	1,204
	FCC (%)	NA (NA, NA)	56 (27, 91)	83 (33, 95)	94 (68, 100)
	Unknown	808	107	163	1,314
	Mean FAD Before	NA (NA, NA)	360 (83, 1,103)	791 (434, 1,357)	918 (498, 1,234)

(continued)

Group	Variable	2016 (N=808)	2017 (N=808)	2018 (N=890)	2019 (N=2960)
	Unknown	808	91	114	1,284
	Mean FAD After	NA (NA, NA)	504 (128, 1,221)	1,093 (704, 1,323)	991 (539, 1,278)
	Unknown	808	145	70	1,426
	FADC	NA (NA, NA)	0.08 (0.01, 0.28)	0.12 (-0.21, 0.46)	0.10 (-0.13, 0.44)
	Unknown	808	173	163	1,516
	FADC (%)	NA (NA, NA)	35 (10, 122)	9 (-29, 83)	16 (-15, 77)
	Unknown	808	173	163	1,516
180 days	FC Before	NA (NA, NA)	73 (2, 185)	35 (1, 150)	19 (2, 86)
	Unknown	808	0	0	10
	FC After	NA (NA, NA)	54 (5, 177)	42 (1, 143)	6 (0, 31)
	Unknown	808	0	0	10
	FCC	NA (NA, NA)	11 (0, 28)	4 (0, 18)	11 (1, 48)
	Unknown	808	0	0	10
	FCC (%)	NA (NA, NA)	16 (6, 36)	21 (12, 38)	82 (47, 99)
	Unknown	808	25	25	122
	Mean FAD Before	NA (NA, NA)	257 (54, 1,134)	482 (115, 1,338)	854 (325, 1,185)
	Unknown	808	9	20	60
	Mean FAD After	NA (NA, NA)	310 (56, 945)	550 (122, 1,225)	998 (547, 1,323)
	Unknown	808	8	0	209
	FADC	NA (NA, NA)	0.00 (-0.10, 0.08)	0.01 (-0.07, 0.06)	0.08 (-0.15, 0.60)
	Unknown	808	9	20	254
	FADC (%)	NA (NA, NA)	2 (-26, 47)	1 (-20, 21)	15 (-19, 132)

(continued)

Group	Variable	2016 (N=808)	2017 (N=808)	2018 (N=890)	2019 (N=2960)
	Unknown	808	9	20	254

[1] Median (IQR); n (%)

Table 36: Summary Statistics for Senegal.

Group	Variable	2017 (N=992)	2018 (N=980)	2019 (N=990)
GWP	SWB (0-10)	5.00 (4.00, 6.00)	5.00 (4.00, 6.00)	5.00 (4.00, 7.00)
	Unknown	34	50	31
	Gender			
	Male	506 (51%)	551 (56%)	491 (50%)
	Female	486 (49%)	429 (44%)	499 (50%)
	Age	30 (22, 43)	30 (22, 42)	30 (22, 41)
	Income	940 (501, 1,963)	983 (493, 1,726)	996 (586, 1,842)
	Urbanicity			
	Rural Area	224 (23%)	190 (19%)	109 (11%)
	Small Town	440 (44%)	450 (46%)	516 (52%)
	Large City	168 (17%)	180 (18%)	208 (21%)
	Suburb	160 (16%)	160 (16%)	157 (16%)
30 days	FC Before	0 (0, 3)	0 (0, 0)	1 (0, 3)
	Unknown	0	30	35
	FC After	0 (0, 3)	0 (0, 0)	0 (0, 5)
	Unknown	0	30	35
	FCC	0 (0, 1)	0 (0, 0)	1 (0, 3)
	Unknown	0	30	35

(continued)

Group	Variable	2017 (N=992)	2018 (N=980)	2019 (N=990)
	FCC (%)	76 (40, 100)	100 (89, 100)	98 (89, 100)
	Unknown	146	401	208
	Mean FAD Before	1,221 (1,030, 1,414)	1,330 (1,211, 1,392)	1,260 (957, 1,413)
	Unknown	110	330	148
	Mean FAD After	1,227 (1,078, 1,446)	1,474 (1,269, 1,550)	1,338 (881, 1,507)
	Unknown	288	466	172
	FADC	0.13 (0.05, 0.41)	0.29 (0.13, 0.52)	0.00 (-0.30, 0.14)
	Unknown	297	634	294
	FADC (%)	12 (4, 46)	30 (11, 74)	0 (-28, 10)
	Unknown	297	634	294
90 days	FC Before	1 (0, 5)	0 (0, 0)	0 (0, 1)
	FC After	1 (0, 3)	0 (0, 0)	0 (0, 0)
	FCC	1 (0, 3)	0 (0, 0)	0 (0, 1)
	FCC (%)	58 (38, 83)	14 (2, 56)	72 (19, 98)
	Unknown	64	519	285
	Mean FAD Before	1,051 (882, 1,375)	1,379 (1,078, 1,510)	1,352 (835, 1,482)
	Unknown	64	438	261
	Mean FAD After	1,175 (995, 1,368)	1,380 (1,202, 1,470)	1,339 (1,201, 1,444)
	Unknown	144	290	244
	FADC	0.16 (0.07, 0.34)	-0.13 (-0.48, 0.00)	0.08 (-0.18, 0.25)
	Unknown	152	438	324
	FADC (%)	17 (10, 41)	-11 (-43, 0)	9 (-13, 51)
	Unknown	152	438	324

(continued)

Group	Variable	2017 (N=992)	2018 (N=980)	2019 (N=990)
180 days	FC Before	3 (0, 7)	0 (0, 1)	0 (0, 0)
	FC After	3 (0, 10)	1 (0, 2)	0 (0, 1)
	FCC	1.25 (0.13, 2.73)	0.02 (0.00, 0.14)	0.00 (0.00, 0.03)
	FCC (%)	41 (26, 55)	10 (5, 41)	10 (6, 23)
	Unknown	16	278	375
	Mean FAD Before	1,039 (783, 1,338)	1,315 (1,149, 1,399)	1,345 (1,223, 1,445)
	Unknown	8	240	370
	Mean FAD After	1,087 (679, 1,320)	1,229 (1,111, 1,421)	1,327 (1,163, 1,410)
	Unknown	48	140	290
	FADC	0.08 (-0.08, 0.16)	-0.19 (-0.31, 0.03)	-0.06 (-0.22, 0.01)
	Unknown	72	255	370
	FADC (%)	8 (-11, 17)	-16 (-24, 9)	-10 (-16, 1)
	Unknown	72	255	370

[1] Median (IQR); n (%)

Table 37: Summary Statistics for Sierra Leone.

Group	Variable	2017 (N=912)	2018 (N=680)	2019 (N=1042)
GWP	SWB (0-10)	4.0 (2.0, 5.0)	4.0 (2.0, 6.0)	3.0 (1.0, 5.0)
	Unknown	30	18	32
	Gender			
	Male	399 (44%)	351 (52%)	479 (46%)
	Female	513 (56%)	329 (48%)	563 (54%)
	Age	30 (21, 45)	29 (21, 42)	30 (21, 45)

(continued)

Group	Variable	2017 (N=912)	2018 (N=680)	2019 (N=1042)
	Income	245 (70, 511)	255 (51, 661)	225 (94, 468)
	Urbanicity			
	Rural Area	174 (19%)	33 (4.9%)	112 (11%)
	Small Town	486 (53%)	505 (74%)	633 (61%)
	Large City	169 (19%)	62 (9.1%)	230 (22%)
	Suburb	83 (9.1%)	80 (12%)	67 (6.4%)
30 days	FC Before	163 (120, 214)	0 (0, 4)	114 (34, 161)
	Unknown	11	452	476
	FC After	182 (90, 226)	1 (0, 42)	15 (2, 61)
	Unknown	11	452	476
	FCC	20 (12, 41)	0 (0, 3)	72 (30, 117)
	Unknown	11	452	476
	FCC (%)	14 (7, 40)	100 (99, 100)	85 (72, 99)
	Unknown	11	509	516
	Mean FAD Before	47 (21, 130)	1,289 (1,114, 1,412)	200 (62, 823)
	Unknown	11	479	506
	Mean FAD After	56 (22, 438)	954 (370, 1,302)	766 (469, 1,097)
	Unknown	11	512	529
	FADC	0.00 (-0.01, 0.12)	-0.21 (-0.78, -0.02)	0.33 (0.18, 0.65)
	Unknown	11	539	579
	FADC (%)	-2 (-24, 66)	-18 (-59, -1)	251 (32, 818)
	Unknown	11	539	579
90 days	FC Before	187 (151, 231)	32 (1, 149)	186 (143, 235)

(continued)

Group	Variable	2017 (N=912)	2018 (N=680)	2019 (N=1042)
	Unknown	0	30	0
	FC After	229 (188, 270)	194 (161, 246)	180 (138, 226)
	Unknown	0	30	0
	FCC	6 (4, 11)	4 (0, 24)	19 (13, 26)
	Unknown	0	30	0
	FCC (%)	4 (2, 7)	14 (9, 17)	11 (7, 15)
	Unknown	0	60	0
	Mean FAD Before	33 (13, 74)	752 (68, 1,265)	40 (14, 85)
	Unknown	0	50	0
	Mean FAD After	22 (7, 91)	41 (12, 85)	41 (16, 96)
	Unknown	0	30	0
	FADC	-0.01 (-0.02, 0.00)	-0.21 (-1.26, -0.02)	0.00 (-0.01, 0.00)
	Unknown	0	50	0
	FADC (%)	-35 (-50, -14)	-83 (-99, -20)	-2 (-10, 10)
	Unknown	0	50	0
180 days	FC Before	239 (199, 276)	226 (199, 269)	240 (195, 280)
	FC After	254 (208, 288)	238 (200, 279)	230 (194, 273)
	FCC	6 (4, 12)	8 (5, 13)	14 (10, 20)
	FCC (%)	3.6 (1.9, 6.4)	4.5 (2.5, 8.7)	6.6 (4.6, 9.0)
	Mean FAD Before	15 (5, 45)	23 (7, 48)	20 (5, 47)
	Mean FAD After	13 (3, 60)	18 (5, 45)	20 (6, 56)
	FADC	-0.002 (-0.005, 0.000)	-0.001 (-0.005, 0.002)	0.000 (-0.003, 0.002)

(continued)

Group	Variable	2017 (N=912)	2018 (N=680)	2019 (N=1042)
	FADC (%)	-16 (-35, -6)	-16 (-36, 12)	8 (-7, 35)

[1] Median (IQR); n (%)

Table 38: Summary Statistics for Togo.

Group	Variable	2016 (N=1000)	2017 (N=1000)	2018 (N=1000)	2019 (N=1130)
GWP	SWB (0-10)	4.0 (2.0, 5.0)	4.0 (3.0, 6.0)	4.0 (3.0, 5.0)	4.0 (2.0, 6.0)
	Unknown	7	38	32	20
	Gender				
	Male	560 (56%)	609 (61%)	579 (58%)	650 (58%)
	Female	440 (44%)	391 (39%)	421 (42%)	480 (42%)
	Age	30 (23, 40)	28 (22, 38)	28 (20, 37)	27 (21, 36)
	Income	390 (173, 780)	606 (252, 1,262)	706 (372, 1,324)	605 (294, 1,202)
	Urbanicity				
	Rural Area	376 (38%)	256 (26%)	340 (34%)	267 (24%)
	Small Town	344 (34%)	432 (43%)	430 (43%)	516 (46%)
	Large City	200 (20%)	232 (23%)	170 (17%)	228 (20%)
	Suburb	80 (8.0%)	80 (8.0%)	60 (6.0%)	119 (11%)
30 days	FC Before	NA (NA, NA)	7 (0, 21)	0 (0, 10)	1 (0, 22)
	Unknown	1,000	632	836	375
	FC After	NA (NA, NA)	0 (0, 3)	0 (0, 1)	5 (1, 18)
	Unknown	1,000	632	836	375
	FCC	NA (NA, NA)	7 (0, 17)	0 (0, 10)	0 (0, 12)
	Unknown	1,000	632	836	375

(continued)

Group	Variable	2016 (N=1000)	2017 (N=1000)	2018 (N=1000)	2019 (N=1130)
	FCC (%)	NA (NA, NA)	100 (90, 100)	100 (100, 100)	64 (36, 86)
	Unknown	1,000	632	836	649
	Mean FAD Before	NA (NA, NA)	856 (492, 1,445)	1,300 (893, 1,461)	1,221 (332, 1,314)
	Unknown	1,000	632	836	579
	Mean FAD After	NA (NA, NA)	951 (389, 1,417)	1,363 (1,100, 1,398)	952 (549, 1,163)
	Unknown	1,000	792	886	421
	FADC	NA (NA, NA)	0.43 (0.10, 0.63)	0.02 (-0.07, 0.26)	-0.49 (-0.58, 0.05)
	Unknown	1,000	792	891	610
	FADC (%)	NA (NA, NA)	76 (22, 121)	1 (-5, 24)	-38 (-47, 39)
	Unknown	1,000	792	891	610
90 days	FC Before	NA (NA, NA)	10 (4, 21)	1 (0, 5)	18 (4, 39)
	Unknown	1,000	192	194	130
	FC After	NA (NA, NA)	2 (0, 4)	7 (2, 18)	6 (2, 20)
	Unknown	1,000	192	194	130
	FCC	NA (NA, NA)	8 (4, 17)	0 (0, 5)	14 (4, 27)
	Unknown	1,000	192	194	130
	FCC (%)	NA (NA, NA)	92 (77, 100)	70 (45, 87)	83 (69, 98)
	Unknown	1,000	192	291	140
	Mean FAD Before	NA (NA, NA)	758 (365, 942)	1,122 (859, 1,376)	811 (472, 1,070)
	Unknown	1,000	192	271	130
	Mean FAD After	NA (NA, NA)	1,011 (820, 1,248)	937 (588, 1,124)	885 (544, 1,102)
	Unknown	1,000	357	194	250
	FADC	NA (NA, NA)	0.49 (0.23, 0.65)	-0.38 (-0.56, -0.09)	0.16 (-0.01, 0.26)

(continued)

Group	Variable	2016 (N=1000)	2017 (N=1000)	2018 (N=1000)	2019 (N=1130)
	Unknown	1,000	357	271	270
	FADC (%)	NA (NA, NA)	66 (35, 141)	-35 (-51, -11)	24 (-1, 45)
	Unknown	1,000	357	271	270
180 days	FC Before	NA (NA, NA)	7 (2, 23)	6 (1, 16)	21 (7, 54)
	Unknown	1,000	0	0	0
	FC After	NA (NA, NA)	27 (7, 62)	11 (4, 56)	16 (7, 44)
	Unknown	1,000	0	0	0
	FCC	NA (NA, NA)	1 (0, 3)	2 (1, 4)	14 (4, 31)
	Unknown	1,000	0	0	0
	FCC (%)	NA (NA, NA)	15 (4, 19)	39 (14, 68)	65 (49, 78)
	Unknown	1,000	0	0	0
	Mean FAD Before	NA (NA, NA)	896 (446, 1,128)	893 (447, 1,174)	656 (346, 917)
	Unknown	1,000	0	0	0
	Mean FAD After	NA (NA, NA)	400 (161, 1,016)	639 (272, 1,101)	705 (445, 911)
	Unknown	1,000	0	0	0
	FADC	NA (NA, NA)	-0.23 (-0.40, -0.11)	-0.06 (-0.29, 0.04)	0.05 (-0.07, 0.23)
	Unknown	1,000	0	0	0
	FADC (%)	NA (NA, NA)	-36 (-60, -15)	-13 (-41, 3)	8 (-12, 48)
	Unknown	1,000	0	0	0

[1] Median (IQR); n (%)

11.7 Spatial Operations

Table 39: Metrics after grid processing.

Pixel Metrics	Definition
Tree cover indicator (reference)	$T_{p,d_i-365} = \mathbf{1}\left(\frac{1}{\tilde{d}}\sum_{d=d_i-365-\tilde{d}}^{d_i-365} P(\texttt{trees}_p = 100\%) \geq \tau\right)$
Tree cover indicator (recall)	$T_{p,d_i} = \mathbf{1}\left(\frac{1}{\tilde{d}}\sum_{d=d_i-\tilde{d}}^{d_i} P(\texttt{trees}_p = 100\%) \geq \tau\right)$
Forest cover indicator (reference)	$F_{p,d_i-365} = \mathbf{1}(p \in \mathcal{N}), \left\lvert \mathcal{N} = \left\{n : \frac{1}{\tilde{d}}\sum_{d=d_i-365-\tilde{d}}^{d_i-365} P(\texttt{trees}_n = 100\%) \geq \tau\right\}\right\rvert \geq 50$
Forest cover indicator (recall)	$F_{p,d_i} = \mathbf{1}(p \in \mathcal{N}), \left\lvert \mathcal{N} = \left\{n : \frac{1}{\tilde{d}}\sum_{d=d_i-\tilde{d}}^{d_i} P(\texttt{trees}_n = 100\%) \geq \tau\right\}\right\rvert \geq 50$
Forest Loss Indicator	$FCC_{p,d_i} = \mathbf{1}\left(FC_{p,d_i} = 0 \vert FC_{p,d_i-365} = 1\right)$
Forest Attrition Distance (reference)	$FAD_{p,d_i-365} = \sqrt{(p-n)^2}, n \in \mathcal{N}, \left\lvert \mathcal{N} = \left\{n : \frac{1}{\tilde{d}}\sum_{d=d_i-365-\tilde{d}}^{d_i-365} P(\texttt{trees}_n = 100\%) \geq \tau\right\}\right\rvert \geq 50$
Forest Attrition Distance (recall)	$FAD_{p,d_i-365} = \sqrt{(p-n)^2}, n \in \mathcal{N}, \left\lvert \mathcal{N} = \left\{n : \frac{1}{\tilde{d}}\sum_{d} P(\texttt{trees}_n = 100\%) \geq \tau\right\}\right\rvert \geq 50$
Forest Attrition Distance Change	$FADC_{p,d_i} = FAD_{p,d_i} - FAD_{p,d_i-365}$

Notes: p indexes pixels, d indexes dates, $\tilde{d}$ is the length of the recall period and d_i is the date of interview i. $P(\texttt{trees} = 100\%)$ is the probability that a given pixel is fully covered by trees; this is provided by the Google Dynamic World dataset. $\tau \in (0, 1)$ is the probability threshold above which a pixel is considered tree-covered. $\mathbf{1}(\cdot)$ is the indicator function and $\mathcal{N}$ is a generic neighborhood of 50 or more tree-covered pixels, which constitutes a forest.

Table 40: Metrics after grid processing.

Aggregate Metrics	Definition
Forest Attrition Distance (reference)	$FAD_{i,d_i-365} = \sum_{p \in \mathcal{P}_i} \frac{\mathsf{A}(p \cap \mathcal{P}_i)}{\mathsf{A}(\mathcal{P}_i)} FAD_{p,d_i-365}$
Forest Attrition Distance (recall)	$FAD_{i,d_i} = \sum_{p \in \mathcal{P}_i} \frac{\mathsf{A}(p \cap \mathcal{P}_i)}{\mathsf{A}(\mathcal{P}_i)} FAD_{p,d_i}$
Forest Cover (reference)	$FC_{i,d_i-365} = \sum_{p \in \mathcal{P}_i} \frac{\mathsf{A}(p \cap \mathcal{P}_i)}{\mathsf{A}(\mathcal{P}_i)} F_{p,di_i-365}$
Forest Cover (recall)	$FC_{i,d_i} = \sum_{p \in \mathcal{P}_i} \frac{\mathsf{A}(p \cap \mathcal{P}_i)}{\mathsf{A}(\mathcal{P}_i)} F_{p,di_i}$
Forest Attrition Distance Change	$FADC_i = \sum_{p \in \mathcal{P}_i} \frac{\mathsf{A}(p \cap \mathcal{P}_i)}{\mathsf{A}(\mathcal{P}_i)} FADC_{p,d_i}$
Forest Cover Loss	$FCC_i = \sum_{p \in \mathcal{P}_i} \frac{\mathsf{A}(p \cap \mathcal{P}_i)}{\mathsf{A}(\mathcal{P}_i)} FCC_{p,d_i}$

Notes: $\mathsf{A}(\cdot)$ is short hand for the surface area, $\mathcal{P}_i$ is the set of pixels (partially) inside the circular buffer around i.

11.8 Additional Regression Output

11.8.1 Polynomial and B-Spline Regression

Table 41: Pooled OLS regression results for 180 days recall period, testing for nonlinear responses.

	(1)	(2)	(3)
FCC	-0.002+	-0.002	
	(0.001)	(0.002)	

(continued)

	(1)	(2)	(3)
FADC	-0.013	-0.003	-0.125
	(0.074)	(0.079)	(0.184)
Age	-0.011^{***}	-0.011^{***}	-0.011^{***}
	(0.001)	(0.001)	(0.001)
Gender [Female]	0.001	0.001	0.002
	(0.022)	(0.022)	(0.022)
Urbanicity [Small Town]	0.160^{***}	0.160^{***}	0.157^{***}
	(0.038)	(0.038)	(0.038)
Urbanicity [Large City]	0.334^{***}	0.334^{***}	0.333^{***}
	(0.059)	(0.059)	(0.059)
Urbanicity [Suburb]	0.290^{***}	0.291^{***}	0.295^{***}
	(0.063)	(0.063)	(0.063)
Income	$0.000+$	$0.000+$	$0.000+$
	(0.000)	(0.000)	(0.000)
FCC × FADC	0.001	0.000	
	(0.001)	(0.002)	
FCC squared		0.000	
		(0.000)	
FCC cubed		0.000	
		(0.000)	
fcc [1st degree]			-0.116
			(0.114)
fcc [2nd degree]			-0.009
			(0.107)
fcc [3rd degree]			-0.138

(continued)

	(1)	(2)	(3)
			(0.113)
fcc [4th degree]			−0.349
			(0.334)
fcc [5th degree]			0.817
			(1.079)
fcc [6th degree]			−2.599
			(2.022)
NA × FADC			−0.139
			−1.753
			0.213
			0.391
			0.588+
			2.781+
			(0.259)
			(0.285)
			(0.309)
			(0.795)
			(1.239)
			(1.586)
Num.Obs.	74 778	74 778	74 778
R2	0.081	0.081	0.082
R2 Adj.	0.073	0.073	0.074
R2 Within	0.005	0.005	0.006
R2 Within Adj.	0.005	0.005	0.006

(continued)

	(1)	(2)	(3)
AIC	$362\,109.7$	$362\,112.7$	$362\,099.4$
BIC	$367\,956.6$	$367\,978.1$	$368\,038.5$
RMSE	2.70	2.70	2.70
Std.Errors	by: ea	by: ea	by: ea
FE: year	X	X	X
FE: adm1	X	X	X
+ p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001			

The graphic below compares the nonlinear partial effects, or dose-response function, of FCC on SWB from column (3) in Table 41 with the linear partial effects from column (5) in Table 3.

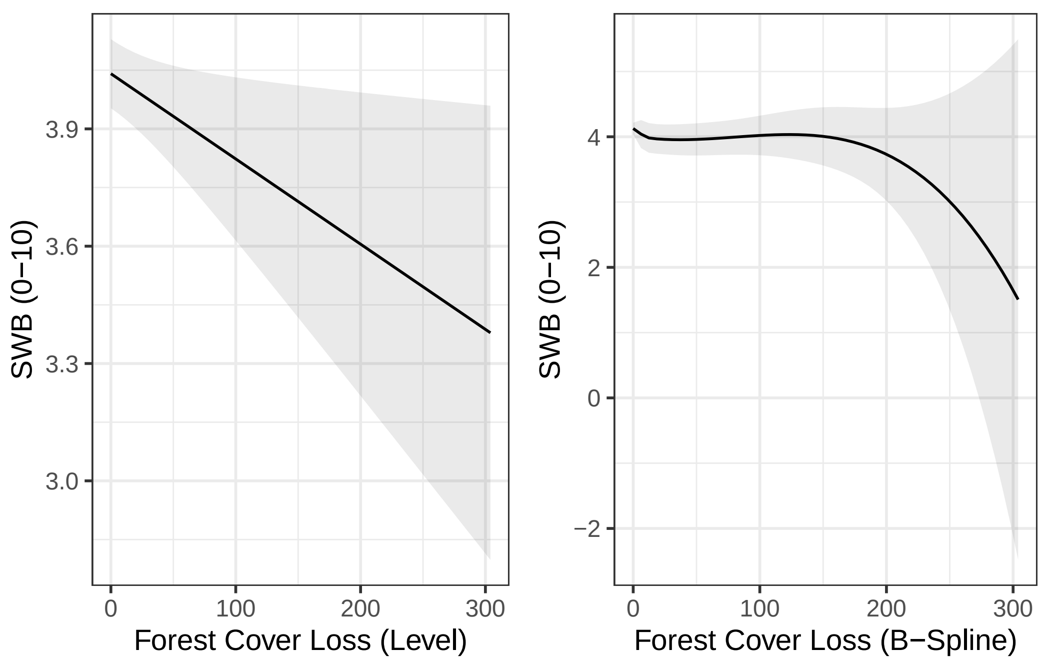


Figure 14: Linear and Nonlinear Partial Effects of Forest Cover Loss.

11.8.2 Ordered Logit and Cumulative Link Mixed Model Estimates

For completeness, I provide ordered logit estimates of the effects of deforestation exposure on SWB.

Table 42: Pooled Ordered Logit and CLMM regression results for 180 days recall period.

	(1)	(2)
0|1	-2.763^{***}	-2.785
	(0.159)	
1|2	-2.091^{***}	-2.113
	(0.147)	
2|3	-1.514^{***}	-1.537
	(0.141)	
3|4	-0.875^{***}	-0.891
	(0.137)	
4|5	-0.357^{**}	-0.360
	(0.136)	
5|6	0.585^{***}	0.600
	(0.137)	
6|7	1.018^{***}	1.035
	(0.138)	
7|8	1.446^{***}	1.464
	(0.141)	
8|9	1.873^{***}	1.890
	(0.146)	
9|10	2.089^{***}	2.108
	(0.149)	
FCC	-0.004	

(continued)

	(1)	(2)
	(0.002)	
FADC	0.012	
	(0.159)	
Age	-0.009^{***}	
	(0.003)	
Gender [Female]	-0.108	
	(0.081)	
Urbanicity [Small Town]	0.146	
	(0.106)	
Urbanicity [Large City]	0.541^{***}	
	(0.110)	
Urbanicity [Suburb]	0.516^{***}	
	(0.151)	
FCC × FADC	0.004	
	(0.003)	
fcc		-0.002
fadc		0.011
age		-0.007
genderFemale		-0.102
urbanSmall Town		0.144
urbanLarge City		0.539
urbanSuburb		0.506
fcc:fadc		0.002
SD (Intercept adm1)		0.866

(continued)

	(1)	(2)
SD (Intercept year)		0.994
Num.Obs.	1874	1874
R2 Marg.		0.014
R2 Cond.		0.354
AIC	8454.0	8487.1
BIC	8553.6	8597.9
RMSE	5.47	5.43

+ p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001

Column (2) includes random effects for year and Adm1 units.

11.8.3 Disaggregated Regression Results by Recall Period

This section presents the results of estimating Equation 3 by OLS with standard errors clustered at the PSU, but estimated on sub- samples (individual regions and countries) and using deforestation exposure variables obtained with 30, 90, and 180 days of recall, respectively.

11.8.3.1 Pooled Data

Table 43: OLS regression results for the entire (pooled) sample, by recall period.

	OLS, 30 days	OLS, 90 days	OLS, 180 days	FE, 30 days	FE, 90 days	FE, 180 days
(Intercept)	3.746^{***}	3.920^{***}	3.963^{***}			
	(0.108)	(0.093)	(0.089)			
FCC	−0.002	0.000	-0.002^{*}	−0.002	0.000	−0.002+
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FADC	0.018	-0.097^{*}	-0.237^{***}	0.007	0.002	−0.019
	(0.044)	(0.049)	(0.065)	(0.045)	(0.051)	(0.074)
Age	-0.042^{***}	-0.046^{***}	-0.044^{***}	-0.038^{***}	-0.041^{***}	-0.040^{***}
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Age Squared	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender [Female]	−0.028	-0.050^{*}	-0.071^{**}	0.088^{**}	0.065^{**}	0.048^{*}
	(0.028)	(0.024)	(0.024)	(0.027)	(0.023)	(0.022)
Urbanicity [Small Town]	0.221^{***}	0.205^{***}	0.250^{***}	0.089^{*}	0.086^{*}	0.122^{**}
	(0.043)	(0.038)	(0.037)	(0.044)	(0.039)	(0.038)
Urbanicity [Large City]	0.551^{***}	0.567^{***}	0.571^{***}	0.220^{***}	0.195^{**}	0.224^{***}
	(0.053)	(0.047)	(0.046)	(0.067)	(0.060)	(0.060)
Urbanicity [Suburb]	0.263^{***}	0.363^{***}	0.397^{***}	0.168^{*}	0.193^{**}	0.216^{***}
	(0.064)	(0.056)	(0.055)	(0.072)	(0.064)	(0.063)
Log Income	0.227^{***}	0.213^{***}	0.206^{***}	0.201^{***}	0.176^{***}	0.167^{***}
	(0.011)	(0.010)	(0.009)	(0.011)	(0.010)	(0.009)
FCC × FADC	0.001	0.000	0.004^{***}	0.001	−0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Num.Obs.	50 755	67 364	72 285	50 755	67 364	72 285
R2	0.030	0.029	0.029	0.100	0.090	0.086
R2 Adj.	0.030	0.029	0.029	0.089	0.082	0.078
R2 Within				0.015	0.013	0.012
R2 Within Adj.				0.015	0.013	0.012
AIC	246 653.9	328 184.5	352 163.6	244 016.6	325 039.7	349 027.9
BIC	246 751.1	328 284.8	352 264.7	249 282.1	330 820.4	354 862.5
RMSE	2.75	2.76	2.76	2.65	2.68	2.68
Std.Errors	by: ea	by: ea	by: ea	by: ea	by: ea	by: ea
FE: adm1				X	X	X
FE: year				X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

11.8.3.2 By Region

Table 44: Results by UN Sub-Region, 30 days recall

	FCC	FADC	FCC × FADC
Eastern Africa	-0.002	-0.032	0.002
	(0.001)	(0.064)	(0.001)
Western Africa	-0.004+	-0.033	0.003
	(0.002)	(0.085)	(0.002)
Middle Africa	0.003	0.115	-0.004^{*}
	(0.002)	(0.101)	(0.002)
Southern Africa	0.000	0.306	-0.009
	(0.006)	(0.215)	(0.011)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

coefficients are presented by variable names in columns and country-regression model in rows.

Table 45: Results by UN Sub-Region, 90 days recall

	FCC	FADC	FCC × FADC
Eastern Africa	-0.001	-0.120	-0.001
	(0.002)	(0.088)	(0.002)
Western Africa	0.000	0.050	-0.002
	(0.002)	(0.085)	(0.002)
Middle Africa	0.002	-0.014	-0.002
	(0.002)	(0.098)	(0.002)
Southern Africa	-0.001	-0.001	-0.003
	(0.004)	(0.222)	(0.007)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

coefficients are presented by variable names in columns and country-regression model in rows.

Table 46: Results by UN Sub-Region, 180 days recall

	FCC	FADC	FCC × FADC
Eastern Africa	0.000	-0.363^{**}	0.004+
	(0.002)	(0.135)	(0.002)
Western Africa	-0.003+	0.065	0.002
	(0.002)	(0.118)	(0.002)
Middle Africa	0.000	-0.007	-0.001
	(0.002)	(0.143)	(0.002)
Southern Africa	-0.006+	0.088	0.011
	(0.003)	(0.228)	(0.010)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: coefficients are presented by variable names in columns and country-regression model in rows.

11.8.3.3 By Country (A-Z)

Table 47: Results by Country, 30 days recall

	FCC	FADC	FCC × FADC
Benin	−0.022*	0.400+	0.011+
	(0.010)	(0.231)	(0.006)
Burkina Faso	−0.017	−0.106	0.021
	(0.017)	(0.193)	(0.027)
Burundi	−0.025*	−0.604	0.041*
	(0.012)	(0.674)	(0.019)
Cameroon	0.007*	0.111	−0.006
	(0.003)	(0.238)	(0.004)
Central African Republic	0.002	0.217	−0.001
	(0.046)	(0.464)	(0.036)
Chad	0.007	−0.270	−0.005
	(0.007)	(0.375)	(0.004)
Congo (Kinshasa)	−0.021	0.964	0.040
	(0.019)	(0.702)	(0.029)
Congo Brazzaville	−0.006	0.236	0.010
	(0.009)	(0.174)	(0.009)
Ethiopia	−0.005	0.010	−0.003
	(0.006)	(0.136)	(0.009)
Gabon	−0.009*	−0.043	0.004
	(0.004)	(0.328)	(0.004)
Ghana	0.003	−0.333	0.000
	(0.005)	(0.255)	(0.004)
Guinea	−0.014	−0.608	0.027**

Table 47: Results by Country, 30 days recall *(continued)*

	FCC	FADC	FCC × FADC
	(0.009)	(0.416)	(0.008)
Ivory Coast	−0.002	0.279	−0.001
	(0.009)	(0.396)	(0.007)
Kenya	0.007	−0.200	0.004
	(0.005)	(0.184)	(0.005)
Lesotho	−0.121	0.801	1.623*
	(0.111)	(1.213)	(0.649)
Liberia	0.003	0.535	−0.051+
	(0.020)	(0.329)	(0.030)
Madagascar	0.000	0.001	−0.002
	(0.003)	(0.195)	(0.003)
Malawi	−0.003	0.062	0.005
	(0.014)	(0.459)	(0.025)
Mali	0.007	0.148	−0.013
	(0.012)	(0.292)	(0.013)
Mauritania	−0.009	0.550	−0.139
	(0.024)	(1.282)	(0.468)
Mozambique	−0.003	0.366	0.002
	(0.006)	(0.361)	(0.014)
Namibia	0.005	0.020	−0.014
	(0.006)	(0.227)	(0.011)
Niger	0.067*	−1.585	−0.069
	(0.029)	(0.965)	(0.067)
Nigeria	−0.003	0.021	−0.003

Table 47: Results by Country, 30 days recall *(continued)*

	FCC	FADC	FCC × FADC
	(0.011)	(0.263)	(0.013)
Rwanda	−0.005	−0.048	0.009
	(0.005)	(0.142)	(0.006)
Senegal	−0.018*	−0.188	0.009
	(0.007)	(0.233)	(0.013)
Sierra Leone	−0.001	0.019	−0.002
	(0.004)	(0.447)	(0.004)
South Sudan	−0.024	1.523**	0.006
	(0.018)	(0.454)	(0.012)
Tanzania	0.004	−0.028	−0.008
	(0.005)	(0.218)	(0.007)
Togo	−0.026+	−0.457	0.038
	(0.014)	(0.512)	(0.026)
Uganda	−0.004	−0.042	0.002
	(0.003)	(0.190)	(0.002)
Zimbabwe	−0.006+	−0.377	0.007
	(0.004)	(0.390)	(0.006)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: coefficients are presented by variable names in columns and country-regression model in rows.

Table 48: Results by Country, 90 days recall

	FCC	FADC	FCC × FADC
Benin	0.012	0.040	−0.016

Table 48: Results by Country, 90 days recall *(continued)*

	FCC	FADC	FCC × FADC
	(0.011)	(0.244)	(0.012)
Burkina Faso	-0.034^{*}	0.314	0.022
	(0.015)	(0.251)	(0.017)
Burundi	0.013	-5.864	-0.127
	(0.014)	(3.953)	(0.153)
Cameroon	0.000	0.025	0.001
	(0.004)	(0.194)	(0.004)
Central African Republic	0.049^{***}	0.147	-0.145^{***}
	(0.013)	(0.501)	(0.030)
Chad	0.009	-0.037	-0.011
	(0.007)	(0.346)	(0.014)
Congo (Kinshasa)	-0.007+	0.328	0.000
	(0.003)	(0.413)	(0.002)
Congo Brazzaville	0.014^{*}	-0.732^{*}	-0.008
	(0.006)	(0.288)	(0.008)
Ethiopia	-0.004	-0.124	0.008^{*}
	(0.005)	(0.183)	(0.004)
Gabon	-0.001	0.020	0.002
	(0.003)	(0.144)	(0.003)
Ghana	0.002	-0.246	0.001
	(0.004)	(0.327)	(0.003)
Guinea	0.000	0.587+	-0.001
	(0.007)	(0.327)	(0.006)
Ivory Coast	-0.005	0.424	-0.001

Table 48: Results by Country, 90 days recall *(continued)*

	FCC	FADC	FCC × FADC
	(0.005)	(0.304)	(0.003)
Kenya	0.002	−0.239	−0.006
	(0.005)	(0.271)	(0.006)
Lesotho	−0.037	2.227	2.994***
	(0.071)	(1.546)	(0.887)
Liberia	0.001	−0.225	−0.003
	(0.004)	(0.323)	(0.003)
Madagascar	−0.001	0.069	−0.010
	(0.004)	(0.211)	(0.007)
Malawi	−0.003	−1.804	0.026
	(0.010)	(1.143)	(0.022)
Mali	0.004	−0.438	−0.010
	(0.017)	(0.353)	(0.052)
Mauritania	0.004	−0.905	−0.003
	(0.012)	(1.091)	(0.226)
Mozambique	0.004	1.811	−0.058
	(0.007)	(1.182)	(0.046)
Namibia	0.003	−0.350	−0.010
	(0.004)	(0.228)	(0.007)
Niger	0.097*	−2.330*	0.211
	(0.041)	(0.903)	(0.151)
Nigeria	−0.001	0.390	−0.001
	(0.007)	(0.243)	(0.006)
Rwanda	0.007	−0.067	−0.001

Table 48: Results by Country, 90 days recall *(continued)*

	FCC	FADC	FCC × FADC
	(0.007)	(0.419)	(0.010)
Senegal	-0.005	-0.222	0.008
	(0.005)	(0.266)	(0.010)
Sierra Leone	0.002	-0.275	-0.014
	(0.009)	(0.394)	(0.032)
South Sudan	0.010	0.287	-0.009
	(0.009)	(0.852)	(0.010)
Tanzania	-0.001	-0.046	0.000
	(0.005)	(0.238)	(0.007)
Togo	-0.009	-0.193	0.013+
	(0.009)	(0.278)	(0.008)
Uganda	-0.001	-0.557*	0.001
	(0.004)	(0.268)	(0.006)
Zimbabwe	-0.010+	0.834	0.000
	(0.005)	(0.702)	(0.010)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: coefficients are presented by variable names in columns and country-regression model in rows.

Table 49: Results by Country, 180 days recall

	FCC	FADC	FCC × FADC
Benin	0.002	0.021	-0.002
	(0.017)	(0.480)	(0.049)
Burkina Faso	-0.073+	-0.301	0.184*

Table 49: Results by Country, 180 days recall *(continued)*

	FCC	FADC	FCC × FADC
	(0.040)	(0.267)	(0.071)
Burundi	0.033	−4.514	−0.427
	(0.022)	(4.870)	(0.328)
Cameroon	0.012	0.122	−0.059*
	(0.009)	(0.323)	(0.024)
Central African Republic	0.003	−6.757	−0.293
	(0.012)	(8.975)	(0.196)
Chad	−0.013+	0.274	0.020*
	(0.007)	(0.379)	(0.010)
Congo (Kinshasa)	−0.003	−0.906	0.000
	(0.005)	(0.759)	(0.011)
Congo Brazzaville	0.015+	−0.717*	−0.014
	(0.008)	(0.336)	(0.010)
Ethiopia	0.002	−0.686*	0.044
	(0.005)	(0.327)	(0.028)
Gabon	0.000	−0.001	0.000
	(0.002)	(0.223)	(0.002)
Ghana	−0.007+	−0.020	0.006*
	(0.004)	(0.433)	(0.003)
Guinea	0.007	0.228	0.001
	(0.008)	(0.432)	(0.003)
Ivory Coast	−0.005+	0.530	0.003
	(0.003)	(0.594)	(0.002)
Kenya	0.007	−0.345	−0.020

Table 49: Results by Country, 180 days recall *(continued)*

	FCC	FADC	FCC × FADC
	(0.007)	(0.593)	(0.031)
Lesotho	−0.029	2.165	−0.183
	(0.039)	(1.339)	(0.452)
Liberia	0.014**	−0.720	−0.012+
	(0.005)	(0.480)	(0.007)
Madagascar	−0.009*	0.285	−0.002
	(0.004)	(0.294)	(0.011)
Malawi	−0.018	−1.108	0.096*
	(0.011)	(1.102)	(0.042)
Mali	−0.007	0.620	0.010
	(0.009)	(0.476)	(0.022)
Mauritania	−0.905+	4.930	1.279
	(0.461)	(4.202)	(0.946)
Mozambique	−0.001	−0.356	0.076
	(0.008)	(1.386)	(0.111)
Namibia	−0.005	−0.130	0.010
	(0.003)	(0.245)	(0.010)
Niger	0.158+	0.069	−3.762**
	(0.089)	(1.027)	(1.318)
Nigeria	−0.003	0.269	−0.003
	(0.004)	(0.246)	(0.004)
Rwanda	0.005	−0.110	0.021
	(0.006)	(0.939)	(0.038)
Senegal	−0.022	−0.046	0.021

Table 49: Results by Country, 180 days recall *(continued)*

	FCC	FADC	FCC × FADC
	(0.014)	(0.273)	(0.018)
Sierra Leone	-0.014	-1.548	0.202
	(0.017)	(4.756)	(1.176)
South Sudan	-0.002	-1.748	0.140
	(0.016)	(1.967)	(0.102)
Tanzania	0.001	-0.105	0.002
	(0.004)	(0.348)	(0.004)
Togo	0.005	0.965^{*}	-0.005
	(0.010)	(0.373)	(0.014)
Uganda	0.003	-0.633^{*}	-0.014
	(0.005)	(0.320)	(0.015)
Zimbabwe	-0.002	-0.331	0.005
	(0.005)	(0.748)	(0.014)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: coefficients are presented by variable names in columns and country-regression model in rows.

11.9 Declaration of Originality

By signing this statement, I hereby acknowledge that the submitted MSc Thesis title "Does Exposure to Deforestation Affect Subjective Well-Being? Evidence from Sub-Saharan Africa" to be produced independently by me, without external help.

Wherever I paraphrase or cite literally, a reference to the original source (journal, book, report, internet, etc.) is provided.

By signing this statement, I explicitly declare that I am aware of the fraud sanctions as stated in the Education and Examination Regulatons (EERs) of SBE, Maastricht University.

Place: Cruz de Pau, Portugal

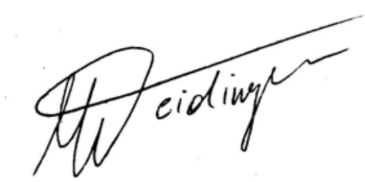
Date: June 16, 2023

Name: Mathias Weidinger

Study Programme: Economic and Financial Research

ID Number: i6113552

Signature:



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