

**QUANTITATIVE APPROACHES TOWARDS EVALUATING THE GLOBAL
BURDEN OF MENTAL ILLNESS**

by

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Abstract

Mental disorders are a leading cause of morbidity and mortality, affecting over one billion people worldwide. This burden, across all levels of socioeconomic development, is rising, yet the majority of people living with a mental disorder do not have access to adequate mental health services, with many facing stigma and high out-of-pocket payments for their care. Moreover, new and emerging dangers such as climate change and the COVID-19 pandemic pose additional stressors that threaten to exacerbate this burden.

This dissertation aims to contribute to a better understanding of the evolving burden and dynamics of global mental health. The three studies it presents take as their focus different quantitative aspects of how the global burden is measured and evaluated, how it may be changing in response to global challenges, and how novel data sources may help in characterizing these changes, particularly in the absence of robust, high-frequency epidemiological surveillance.

In Chapter 1, we investigated the share of the global burden of disease attributable to mental disorders and its associated economic value. To capture premature mortality due to mental disorders, as well as disability from associated causes, we proposed a composite approach to estimation. Using the most recently available estimates from the Global Burden of Disease study, we found that the burden of mental disorders is likely much higher than previously estimated, encompassing 16% of disability-adjusted life years in 2019. The economic value of this mental health burden was estimated to exceed 4.7 trillion USD using a value of statistical life year approach, accounting for

regional losses that range from 3.9% of gross domestic product in Eastern Sub-Saharan Africa to 7.9% in High-income North America.

In Chapter 2, we focused on Madagascar—a low income country that is among the most vulnerable to the health consequences of climate change—and examine how health system visits for mental disorders may be shifting in response to climate change exposures such as changes in temperature, soil moisture, and the duration of tropical storms and cyclones. Drawing on meteorologic, geospatial, and health system data reported by 3,413 facilities from 2010 to 2020, we conducted an ecological analysis using negative binomial regression. Our results indicated that warmer temperatures in the cooler central highlands were associated with a decrease in monthly reported visits for mental disorders, while higher soil moisture could lead to an increase in visits, particular in high flood-risk regions and after a three-month lag, indicating potential variation in the impact of climate change on mental health needs and system responses.

In Chapter 3, I investigated how Google search data for mental health symptoms might provide insight into the state of mental health during the COVID-19 pandemic. Using an interrupted time series approach with search data from U.S. counties, states, and international trends, I found that announcements of COVID-19 vaccine safety and efficacy data in November 2020 were associated with immediate and sustained declines in search density for anxiety and depression. These declines in searches, if taken as a reasonable proxy for population mental health, underscore the importance of timely and transparent communication and illustrate the potential application of high frequency internet search data for population mental health surveillance.

Taken together, these chapters highlight different facets of the global burden of mental disorder and contribute to a growing effort to generate a more comprehensive understanding of the challenges posed by this burden at local, regional, and global levels.

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* * *

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To the steps we have taken already, love, and to the many we have ahead.

* * *

Introduction

Mental health is an essential part of human flourishing. As defined by the World Health Organization (WHO), it encompasses “a state of well-being in which every individual realizes [their] own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to [their] community”.¹

For much of the global population, however, attaining this state of mental health is an enduring challenge, with over one billion people worldwide living with a mental or addictive disorder.² Mental disorders are a leading cause of disability,^{2,3} with the Global Burden of Disease (GBD) study estimating that 4.9% of disability-adjusted life years (DALYs) and 14.6% of years lived with disability (YLDs) were attributable to mental disorders in 2019.⁴ Mental disorders are also closely linked to physical health and can be a significant risk factor for premature mortality.⁵ Among patients living with the most severe mental illnesses, premature mortality may reduce life expectancy by as much as 10 to 20 years.⁶

At all levels of sociodemographic development, this burden is rising.⁷ Yet despite this global scale and despite a growing evidence base for impactful, cost-effective interventions that may help,⁸ the profound impact of mental disorders has been met by a profound treatment gap.⁹ A majority of the world’s population lives in countries with fewer than 10 psychiatrists for every 100,000 people (Figure 1). Most of those living with a mental disorder do not have access to adequate care,^{9,10} and many face stigma,^{11,12} discrimination,^{13,14} and abuse.¹⁵⁻¹⁷

2

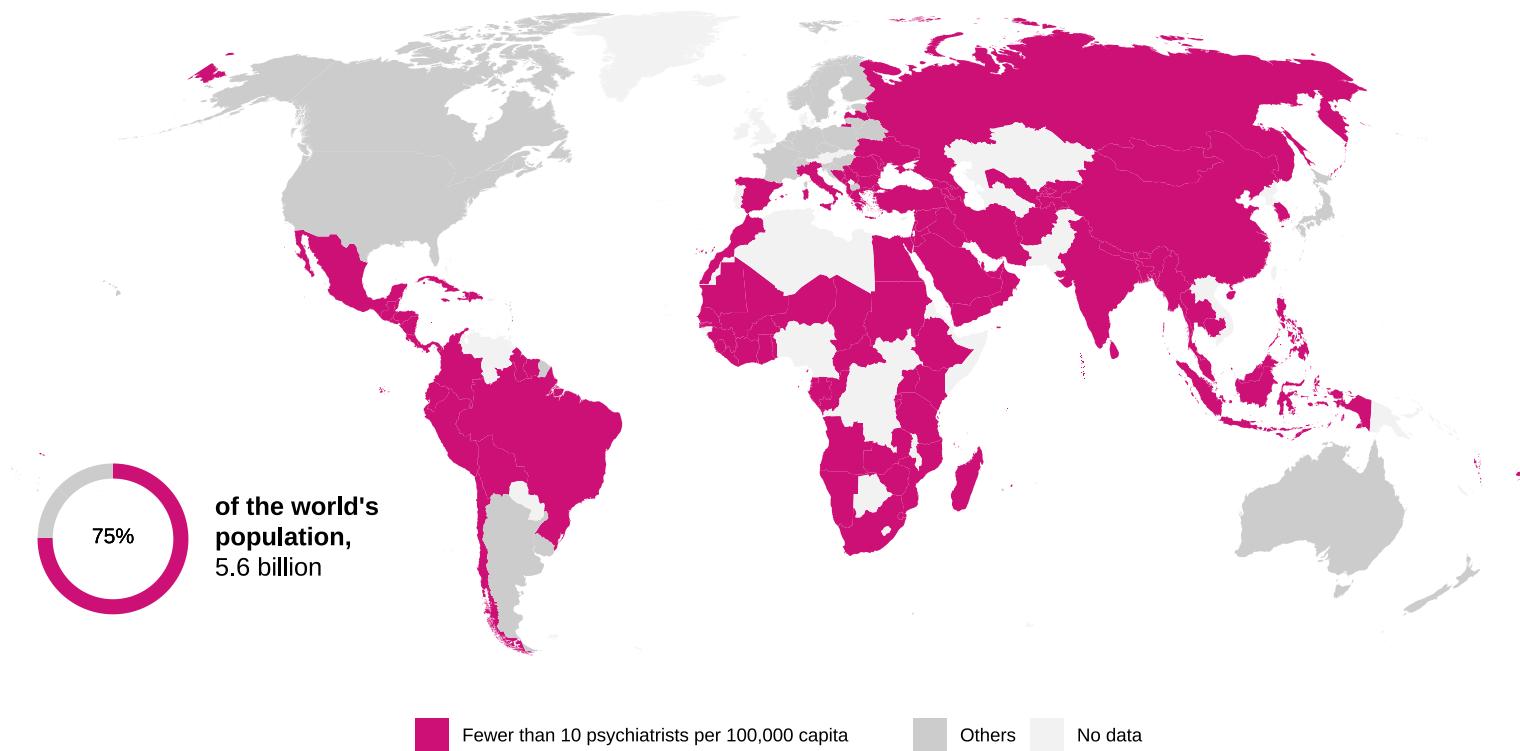


Figure 1: Countries where fewer than 10 psychiatrists per 100,000 capita were working in the health sector between 2013-2017, average. Data from the Global Health Observatory (GHO) of the World Health Organization (WHO).

In addition to the long-standing challenges of these unmet needs, new and emerging dangers such as climate change and COVID-19 reveal additional stressors that threaten to exacerbate this burden. Global climate change—an accelerating existential threat to planetary health that the United Nations considers the “defining crisis of our time”—is already manifesting profound impacts on mental health.¹⁸ These impacts are shaped both by the disastrous upheaval caused by worsening extreme weather events and by the incremental change rising temperatures and sea levels have wrought on livelihoods and means of living—altering the availability and access to natural resources, land use, infrastructure, and community.^{19,20} The essential connections between mental health and human well-being have been further underscored by the devastating impacts of the COVID-19 pandemic, which continues to deal psychological and psychiatric harm to patients, health care workers, and the public overall.²¹

The extant and evolving challenges of global mental health, in turn, entail jeopardy to health systems and to the three intrinsic goals of improving health, responsiveness, and financial protection.²² According to the WHO’s Mental Health Atlas report from 2020, mental health system governance, capacity, and integration into routine service delivery is fundamentally lacking across nations of all levels of economic development, with only 15% of countries having functional integration of mental health into primary health care.²³ This lack of service delivery echoes a lack of basic epidemiological data,²⁴ constraining research and frustrating efforts to respond to mental health needs. Among nations, the Atlas report highlights widening disparities in health system indicators, with worsened gaps in service availability and public health expenditure for mental health between low- and middle-income countries and high-income peers. With respect to health spending, mental health care services in many countries have traditionally relied primarily or exclusively on out-of-pocket payments,²⁵ resulting in a greater risk of catastrophic health expenditure among households with patients living with a mental disorder. These direct costs, when coupled with the indirect costs of

diminished earnings due to disability, may exacerbate conditions of poverty,²⁶ which, in turn, may lead to worsening mental health²⁷—feeding a vicious cycle that harms households and nations alike.

A better understanding of the evolving burden and dynamics of global mental health may thus have broad consequences to strengthening health system responses to mental disorders and improving health outcomes for millions of individuals worldwide. Contributing to such an understanding has motivated this dissertation, which takes as its focus different quantitative aspects of the global burden of mental illness—how we measure and evaluate it, how it may be changing, and how novel data sources may help in characterizing it, particularly in the absence of robust, high-frequency epidemiological surveillance. The papers presented in the subsequent three chapters echo the interdisciplinary nature of global mental health, drawing on a broad range of quantitative methods and applying analytic tools and insights from epidemiology, health economics, and econometrics.

In Chapter 1, we investigated the share of the global burden of disease attributable to mental disorders and its associated economic value. We reviewed recent efforts to estimate both the epidemiologic and economic burden of mental disorders, and we propose a composite approach to estimation to capture a broader share of attributable morbidity and mortality.^{3–5,28–30} Applying this approach using the most recently available GBD data, we estimated that the global burden of mental disorders is likely much higher than previously estimated, encompassing 16% of disability-adjusted life years in 2019. Using value of statistical life approaches, we estimated that the economic value of this burden would exceed 4.7 trillion USD.

In Chapter 2, we investigated how health system visits for mental disorders in Madagascar may be shifting in response to changes in climate. Madagascar has little to no mental health surveillance data and is among the nations most vulnerable to climate change. To address these gaps, we studied the impact of three climate change exposures—temperature, soil moisture, and duration of cyclones and tropical storms—by leveraging meteorologic, geospatial, and health system data reported by

3,413 facilities from 2010 to 2020. We found a statistically significant reduction in monthly mental health related visits associated with each degree Celcius increase in temperature, primarily localized to facilities in the central highlands, where cooler temperatures are more prevalent. We further found that higher soil moisture may be associated with more mental health visits in the future, after a three month lag; this increase was primarily found in the eastern lowlands and the northern dry deciduous forests, consistent with the geographic concentration of flood risk in Madagascar. Our findings point to potential heterogeneity in how changing climate conditions will impact mental health needs and system responses.

In Chapter 3, I investigated how internet search data for health symptoms might provide high frequency insight into the state of population mental health during the COVID-19 pandemic. Using search data from U.S. counties, states, and international trends, I explored how announcements of COVID-19 vaccine safety and efficacy data in November 2020 impacted Google search trends for mental health symptoms. I found evidence of statistically significant immediate and sustained declines in searches for anxiety, depression, and major depressive disorder throughout the 40 days following these announcements. The findings underscore the importance of timely and transparent communication and illustrate the potential application of high frequency internet search data for population mental health surveillance.

Overall, these three chapters highlight different facets of the global burden of mental disorders and speak to the interconnectedness of mental health and human well-being, as well as the urgent need for greater research and resources to better illuminate such pathways. Taken together, they contribute to a growing effort to generate a more comprehensive understanding of the challenges posed by this burden—as well as opportunities for improving mental health at local, regional, and global levels.

1 Quantifying the global burden of mental disorders and their economic value

Daniel Arias, Shekhar Saxena, and Stéphane Verguet

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Background: Epidemiological and economic estimates suggest that the global burden of mental disorders is considerable, both in its impacts on human health and losses to societal welfare. The availability of additional data and the emergence of new approaches present an opportunity to examine these estimates, which form a critical part in making the investment case for mental health.

Methods: This study reviews, develops, and incorporates new estimates and methods in quantifying the global burden of mental illness. Using a composite estimation approach that accounts for premature mortality due to mental disorders and additional sources of morbidity and applying a value of a statistical life approach to economic valuation, we determine global and regional estimates of the economic cost that can be associated with mental disorders, building on data from the 2019 Global Burden of Disease study.

Findings and interpretation: We estimate that 418 million disability-adjusted life years (DALYs) could be attributable to mental disorders in 2019 (16% of global DALYs), a more than three-fold increase compared to conventional estimates. The economic value associated with this burden is estimated at about USD 4.7 trillion. At a regional level, the losses account for between 3.9% of gross domestic product in Eastern Sub-Saharan Africa and 7.9% in High-income North America. Taken together, our findings suggest that the burden of mental illness in terms of both health and economic losses may be much higher than previously assessed.

Keywords: mental health, disease burden, premature mortality, economic burden.

1.1 Introduction

A growing body of literature suggests that mental disorders are costly, both in the direct medical costs of care, outpatient visits, and hospitalizations, and in indirect costs, such as losses in income and productivity due to disability, which may cause absenteeism and presenteeism.³¹ These costs further worsen conditions of poverty²⁶—a vulnerability that, in turn, worsens mental health, feeding a vicious cycle of poverty and illness.²⁷ At the national level, mental disorders deplete the supply of labor and capital, resulting in poorer economic output.³² Among households and nations alike, the burden of mental illness thus has considerable economic consequences and poses a challenge to both health and wealth.

Evaluating the economic burden of mental illness is a critical part in making the investment case for global mental health, informing public health decision-making, and guiding priority-setting and the scale up of much-needed interventions.³³ At the global level, however, the most recent estimate of the economic impact of mental disorders was published in 2011, using burden of disease estimates from 2004.²⁸ This landmark paper by Bloom and colleagues estimated that the value of losses due to mental disorders was roughly 1.3 trillion USD in 2010 (1.6 trillion USD in 2019) when DALYs were valued at one times GDP per capita.²⁸ The authors further projected that these losses would grow to nearly 2.5 trillion USD 2010 (or approximately 3.0 trillion USD in 2019) by 2030. (See Tables S1.1 and S1.2 in Appendix 1 for estimates from the other two approaches.) These estimates have been widely cited in calls to action concerning global mental health.^{7,34}

While the estimates presented from this paper remain staggering and salient, new studies estimating the morbidity and mortality associated with mental illness have since become available.^{5,29,35} These studies suggest that previous (and current) estimates of the global burden of mental disorders may be considerably underestimated, which, in turn, has implications for estimating the true economic burden of mental illness.

The most recent estimates of morbidity and mortality due to mental disorders come from the Global Burden of Disease (GBD) 2019 study.⁴ The GBD study provides disease burden estimates using DALYs, years of life lost (YLLs), and years lived with disability (YLDs), which are then aggregated within a hierarchical grouping scheme that classifies causes of disability and death at different levels of mutually exclusive and completely exhaustive categories. (Mental disorders are a Level 2 condition, nested under noncommunicable diseases (NCDs); see Table S1.3.)

While GBD remains the gold standard for global epidemiologic estimation, the nature of the GBD scheme—in particular, the rationale for grouping certain conditions under mental disorders or not—has been the subject of debate in the literature.^{29,36,37} In particular, work by Vigo et al. (2016) published in *The Lancet Psychiatry* argues for an expanded classification of mental disorders under the GBD classification scheme to account for underestimation of the burden of mental disorders.²⁹ The authors attribute this underestimation to five main causes: 1) the distinction drawn between mental and neurological diseases; 2) the categorization of self-harm and suicide under injuries; 3) the classification of all chronic pain and somatoform disorders under musculoskeletal disorders; 4) the exclusion of personality disorders; and 5) the exclusion of premature mortality due to mental disorders. Using data from the 2013 GBD study, Vigo and colleagues re-allocated the entire burden of dementias, epilepsy, migraine, tension-type headache, and self-harm to mental disorders. In addition, a third of the burden of musculoskeletal disorders without anatomical correlate (i.e., somatoform disorders with prominent pain) was attributed to mental disorders.²⁹ This reallocation attributed 13% of DALYs to mental disorders, a 6 percentage point increase from the GBD estimate of 7%.

In this paper, we attempt to revisit the estimation of the global burden of mental disorders and of its associated economic value. Our aim is to characterize potential underestimation of the burden of mental disorders and to quantify the economic value of this burden under different estimation

approaches. Specifically, we expand on Vigo et al.²⁹ by capturing premature mortality due to mental disorders using pooled risk ratios of mortality from a systematic review of mental disorders⁵ to determine the population attributable fraction (PAF) of premature mortality. Inclusion of premature mortality through the PAF presents a novel composite approach that can more broadly capture attributable morbidity and mortality. Using this approach on GBD 2019 estimates, we then apply monetary values to DALYs to reach estimates of the global economic value of the mental burden of disease using a value of a statistical life (VSL) approach similar to that of Bloom and colleagues,²⁸ which attempts to capture a population's willingness to pay to reduce morbidity and mortality associated with illness. The VSL approach—in contrast to alternatives such as cost of illness and value of lost output approaches—includes an economic valuation of mortality risk reductions in monetary terms, and thus enables comparison across sectors (beyond the sole health sector) which can motivate decision-making toward ameliorating welfare and societal mental health. Our findings suggest that both the epidemiological and economic burden of mental disorders could be larger than previously estimated, and that underestimation would be larger among regions where premature mortality due to mental disorders is greater.

1.2 Methods

To estimate the economic burden of mental disorders, we first estimate the attributable mental burden of DALYs under various estimation approaches using data from the 2019 GBD study (available from the Global Health Data Exchange at <https://ghdx.healthdata.org/gbd-2019>). Second, we apply a monetary value to a DALY to yield an economic assessment associated with these burden estimates.

1.2.1 Burden of mental disorders

In our analysis, we replicate the approach of Vigo et al. (2016) using GBD 2019 estimates, applying a similar re-allocation formula to YLLs, YLDs, DALYs, and deaths. Our approach, however, differs in some key respects.

First, we agree with Whiteford and colleagues in viewing the assigning of the entire burden of suicide and self-harm to mental disorders as an overestimate, and consequently do not reallocate all DALYs due to suicide towards the mental health burden.³⁷ While it is empirically clear that mental disorders elevate the risk of death by suicide and that the majority of suicides appear to be due to mental disorders,³⁸ we view assigning the entirety of this burden to mental disorders as overinclusive, which we avoid to favor a conservative estimation strategy.

Second, we attempt to capture premature mortality attributable to mental disorders, recognizing that persons with mental disorders are at elevated risk of all-cause mortality,⁵ unnatural death,³⁹ and deaths due to natural causes.⁴⁰ Not capturing this share of mortality is likely to be a prominent cause of underestimating the burden of mental illness, particularly in countries where the dominant share of the DALY burden is mortality (rather than morbidity).

Following Vigo and colleagues, we replicate reallocations in neurological and musculoskeletal conditions, and further include alcohol and mental use disorders, as these were previously classified under mental disorders within the GBD classification.

This provides estimates of YLDs due to mental disorders. We then estimate the PAF of mortality due to mental disorders, using GBD prevalence estimates and relative risk estimates for natural-cause and unnatural-cause mortality generated from a systematic review and meta-analysis by Walker et al.⁵ A comparison of our allocation approach with those of Vigo et al. and the original GBD hierarchical allocation is shown in Table 1.1.

Table 1.1: Comparison of the composite allocation approach with the reallocation approach and with the original Global Burden of Disease (GBD) hierarchical allocation, with respect to the burden of mental disorders

	Original allocation	2. Reallocation approach (Vigo et al. 2016)	3. Composite approach
<i>Schizophrenia</i>	Yes	Yes	Yes
<i>Depressive, bipolar, anxiety disorders</i>	Yes	Yes	Yes
<i>Eating disorders</i>	Yes	Yes	Yes
<i>Autism spectrum, AD(H), and conduct, disorders</i>	Yes	Yes	Yes
<i>Substance abuse disorders</i>	Included in GBD 2016; classified separately since GBD 2017	Yes (with additional deaths due to alcohol use included in Vigo et al. 2020)	Yes
<i>Neurological disorders</i>	No	Yes	Yes
<i>Chronic pain syndrome and somatoform pain disorders</i>	No	Yes, 33% of DALYs	Yes, 33%
<i>Self-harm / suicide</i>	No	Yes, all DALYs	Yes, % of YLLs due to unnatural death based on PAF
<i>Premature mortality due to mental disorders</i>	No	No	Non-communicable diseases: Yes, % of YLLs due to natural death based on PAF Infectious, maternal, and neonatal diseases: No

Our approach to capturing premature mortality relies on a pooled relative risk estimate for mortality by natural and unnatural causes, drawn from 148 studies identified by Walker et al.⁵ These studies collectively reflect over 338,000 deaths across 29 countries and 6 continents. The

majority of deaths (67%) recorded in studies with disaggregated data arose from acute and chronic illnesses, while unnatural causes such as injury and suicide represented 18% of deaths (the rest being unallocated). Overall, the pooled risk of all-cause mortality was 2.2 times higher (95% confidence interval (CI): 2.1-2.3) among people with mental disorders compared to those without. Using this relative risk estimate, Walker and colleagues calculated a PAF to estimate that 8 million deaths were due to mental disorders in 2012.

While Walker and colleagues used a global estimate of the worldwide prevalence of mental disorders in their study to calculate the PAF, we use GBD estimates of prevalence to derive both global- and country-level results. The PAF for a given disorder d and country c is given by:

$$PAF_{(d,c)} = \frac{p_{(d,c)} (RR_d - 1)}{1 + p_{(d,c)} (RR_d - 1)} , \quad (1.1)$$

where $p_{d,c}$ is the prevalence of a given disorder in a country and RR_d is the relative risk of mortality estimated by Walker et al.⁵

We separately estimate the PAF for natural and unnatural causes of mortality. Using the calculated PAF estimates, we estimate YLLs attributable to mental disorders by multiplying the PAF by the national burden of mortality. For natural causes of death, we conservatively apply the PAF against YLLs attributable to NCDs. For unnatural causes of death, we apply the PAF against YLLs due to self-harm and injuries. These YLLs are then combined with the YLDs calculated previously to provide DALYs.

1.2.2 Economic burden of disease

To estimate the economic cost associated with premature mortality and morbidity tied to mental illnesses, we assigned a monetary value to attributable DALYs. VSL approaches assign a monetary value to small reductions in mortality risks.⁴¹ Drawing from these approaches, Jamison and colleagues

have estimated monetary values of statistical life years,⁴² which Khadka and colleagues recently adapted to quantify the economic value of changing mortality risk by cause of death in low- and middle-income countries (LMICs).⁴³ While VSL approaches are not meant to assign monetary values to full life years or years lived with illness or disability,⁴¹ the Copenhagen Consensus has previously implemented the use of GDP per capita as a proxy for the monetary value of a DALY as a standard estimate.⁴⁴ Values of one and three times GDP per capita have been suggested as proxies for the value of a DALY.^{45,46} Estimates of \$1,000 and \$5,000 per DALY have been used, with the justification that these would be reasonable and convenient lower and upper values, particularly for low-income and lower-middle income countries.^{47,48}

Consistent with previous approaches, we use GDP per capita (USD 2019) for our base-case value of a DALY. GDP inputs are reported in 2019 USD and obtained from the World Bank's World Development Indicators; for consistency with our epidemiological inputs, we convert to per capita values using GBD population estimates.

1.2.3 Sensitivity analyses

The primary focus of this paper concerns structural uncertainty in determining the burden of mental illness, resulting in the evaluation of three different estimation approaches. To address parameter uncertainty within each approach, we apply a three-way sensitivity analysis. First, following a simple intuitive approach, we incorporate the upper and lower uncertainty intervals (UIs) provided by GBD 2019 for YLLs, YLDs, and DALYs to account for parameter uncertainty. Second, we use the upper and lower values of prevalence estimates and of the 95% confidence intervals (CIs) of the pooled relative risk of all-cause mortality from Walker and colleagues in our composite approach.⁵ Third, our lower bound estimates are set to reallocate one sixth of the burden of musculoskeletal disorders proposed by Vigo and colleagues,²⁹ while our upper bound estimates are set to reallocate

one half of this burden.

In addition to our base-case economic valuation, we further report our VSL estimates using three times GDP per capita as the value of a DALY. (Alternative valuations using values of \$1,000 and \$5,000, as well as purchasing power parity (PPP)-adjusted GDP per capita, are reported in Tables S1.5 and S1.6 of Appendix 1.)

1.2.4 Statistical analysis

All analyses were completed using R (version 4.2.1).⁴⁹

1.2.5 Ethics statement

The Institutional Review Board (IRB) of the Harvard T.H. Chan School of Public Health determined that this study was not human subjects research and that additional review was not required (protocol number: IRB20-1946, determined on November 13, 2020).

Table 1.2: Disability-adjusted life years (DALYs) attributable to mental disorders as totals (millions) and percentages of overall burden, by World Bank income group classification and GBD region, under three estimation approaches.

	Original approach						Reallocation approach						Composite approach					
	DALYs			% of burden			DALYs			% of burden			DALYs			% of burden		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
Global	125.3	93.0	163.2	4.9	4.1	5.8	321.2	198.6	505.2	12.7	8.7	18.0	417.7	276.7	608.4	16.5	12.1	21.6
High income	24.5	18.1	32.0	6.7	5.7	7.6	74.4	46.2	117.9	20.3	14.4	28.1	81.0	52.8	120.3	22.1	16.5	28.7
Upper-middle income	45.6	33.8	59.7	5.6	4.7	6.4	117.5	69.5	191.6	14.3	9.7	20.5	156.6	99.3	236.2	19.1	13.9	25.3
Lower-middle income	44.9	33.0	58.9	4.3	3.6	4.9	108.8	65.0	174.1	10.4	7.1	14.6	147.4	90.2	225.7	14.1	9.8	18.9
Low income	10.1	7.4	13.5	3.4	2.9	3.8	20.3	12.0	32.6	6.7	4.6	9.3	32.3	19.8	49.9	10.7	7.7	14.2
East Asia	21.0	15.7	27.3	5.3	4.5	6.0	55.8	32.8	91.8	14.1	9.5	20.3	72.7	45.6	109.7	18.3	13.2	24.3
Southeast Asia	9.1	6.7	11.9	4.6	3.9	5.3	23.3	12.4	40.4	11.8	7.2	17.8	32.3	18.8	52.0	16.3	11.0	22.9
Oceania	0.2	0.1	0.2	3.0	2.7	3.3	0.4	0.2	0.6	7.1	4.7	9.8	0.6	0.4	1.0	12.2	8.6	16.2
Central Asia	1.3	0.9	1.7	4.4	3.7	5.1	3.7	2.3	5.8	13.1	9.3	17.8	4.7	2.9	7.2	16.4	11.8	22.0
Eastern Europe	3.5	2.6	4.5	3.9	3.3	4.5	13.4	9.0	20.2	15.1	11.5	20.0	16.1	10.7	23.5	18.1	13.6	23.3
Central Europe	1.7	1.3	2.3	4.3	3.7	4.8	5.7	3.4	9.4	14.1	10.0	19.9	6.8	4.2	10.5	16.8	12.2	22.3
Caribbean	0.8	0.6	1.0	5.2	4.5	5.8	1.7	1.0	2.8	11.7	8.2	16.0	2.7	1.7	4.1	18.0	13.3	23.5
Central Latin America	4.1	3.0	5.5	6.2	5.3	7.0	10.1	5.9	16.4	15.1	10.4	21.0	14.2	8.9	21.8	21.3	15.5	27.9
Tropical Latin America	5.1	3.7	6.6	7.5	6.2	8.8	11.6	7.0	18.6	17.3	11.7	24.7	16.9	11.7	24.1	25.2	19.5	32.1
Andean Latin America	1.1	0.8	1.4	7.0	6.1	7.8	2.3	1.4	3.8	15.0	10.5	20.3	3.2	1.9	4.9	20.4	14.9	26.7
North Africa and Middle East	10.7	7.8	14.1	8.0	6.9	9.0	21.5	12.3	35.3	16.0	10.8	22.5	31.3	19.3	48.1	23.4	17.0	30.7
Southern Sub-Saharan Africa	1.2	0.9	1.6	3.2	2.6	3.8	3.2	2.0	4.9	8.3	5.7	11.6	4.7	3.1	6.8	12.3	9.0	16.1
Western Sub-Saharan Africa	6.7	4.9	9.0	2.6	2.2	2.9	14.7	8.2	24.5	5.6	3.6	8.0	20.8	11.9	33.5	7.9	5.3	10.9
Central Sub-Saharan Africa	2.1	1.5	2.8	3.7	3.1	4.2	4.1	2.4	6.6	7.2	4.9	9.9	6.4	3.8	9.9	11.0	7.7	14.8
Eastern Sub-Saharan Africa	5.8	4.2	7.7	3.5	2.9	4.0	11.3	6.9	17.8	6.8	4.8	9.2	15.8	9.9	24.2	9.5	6.8	12.6
South Asia	28.8	21.2	37.6	4.6	3.8	5.3	70.8	43.3	111.1	11.2	7.7	15.6	96.0	59.9	144.2	15.2	10.7	20.2
Southern Latin America	1.3	0.9	1.6	6.9	5.7	8.1	3.1	1.9	4.8	16.9	11.9	23.5	3.8	2.6	5.5	21.1	16.0	27.0
Western Europe	9.4	7.0	12.4	7.5	6.3	8.6	25.6	15.3	41.9	20.2	13.8	29.0	28.5	18.4	42.6	22.5	16.6	29.5
High-income North America	8.0	6.0	10.4	6.6	5.6	7.6	27.1	18.1	40.7	22.4	17.0	29.7	29.0	19.5	41.7	23.9	18.3	30.4
Australasia	0.7	0.5	0.9	9.5	8.1	10.8	1.7	1.1	2.6	22.9	17.0	30.5	1.9	1.3	2.7	25.2	19.7	31.4
High-income Asia Pacific	2.7	2.0	3.5	5.4	4.5	6.1	9.8	5.7	16.3	19.6	13.1	28.4	9.1	5.8	13.8	18.1	13.2	24.0

1.3 Results

Under GBD 2019, over 125 million DALYs were attributed to mental disorders, or roughly 5% of the global burden. After including alcohol and drug use, neurological disorders, chronic pain, suicide, and self-harm, the share due to mental disorders rose to 12% of global DALYs (approximately 321 million DALYs). Under the composite approach, an additional 97 million DALYs were attributed to mental disorders, encompassing, in total, over 16% of global DALYs (Figure 2). Under all three methods, the burden of mental disorders (in DALYs) exhibited a country-income gradient, with mental disorders comprising over twice the burden of disease in high-income countries compared to low-income countries.

Rates of DALYs and deaths attributable to mental disorders under the different estimation approaches are presented by GBD region (Figure 3). Geographically, the composite approach allocated a large portion of DALYs (to mental disorders) in Eastern Europe, North and Latin America, and sub-Saharan Africa. This is largely driven by the inclusion of premature mortality in the composite approach. Estimates of DALYs by country income group and GBD region are reported in Table 1.2. (Estimates of deaths are reported in Table S1.4-1.6.)

Under the three approaches, we calculated the economic value of mental disorder losses (Table 1.3). Using GDP per capita as a proxy for the value per DALY, economic losses due to mental disorders were estimated at 4.7 trillion USD using our composite approach. This estimate is 1.1 trillion USD larger than that reached using the 2016 reallocation approach and over 3.3 trillion USD larger than that reached from the unadjusted GBD 2019 estimates.. Further adjusting for purchasing power parity, the global value of mental illness losses would exceed 7.2 trillion international dollars in 2019 (Table S1.7).

Table 1.3: Global economic value associated with premature mortality and morbidity from mental disorders, by estimation approach and value per DALY. Estimates are in trillions 2019 USD. DALY: disability-adjusted life year. USD: United States dollar. GDP: gross domestic product.

Value per DALY (USD, 2019)	Original approach			Reallocation approach			Composite approach		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
<i>1x GDP/capita</i>	1.42	1.06	1.85	3.64	2.25	5.73	4.74	3.14	6.90
<i>3x GDP/capita</i>	4.27	3.17	5.55	10.93	6.76	17.20	14.22	9.42	20.71

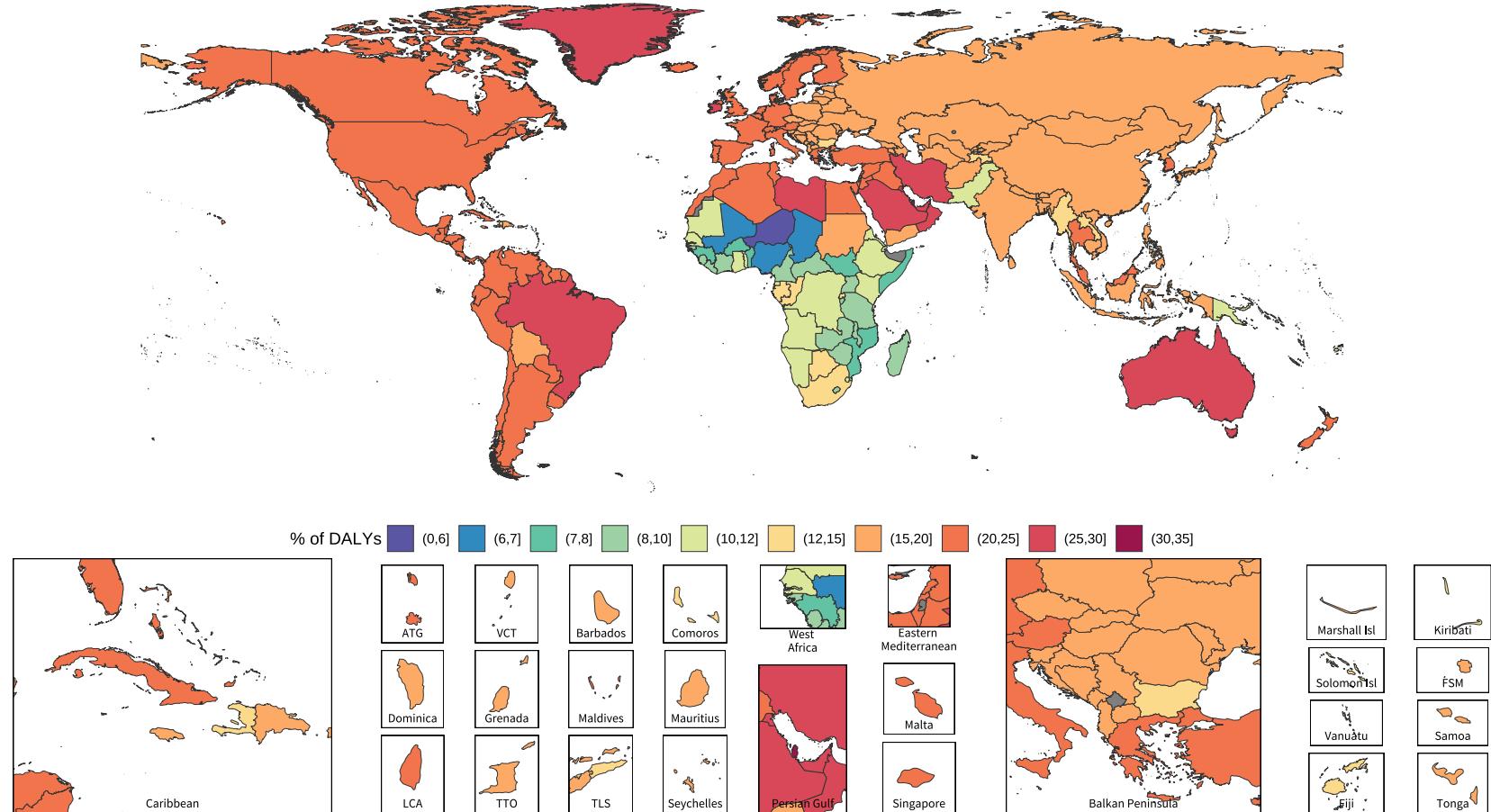


Figure 2: Disability-adjusted life years (DALYs) attributable to mental disorders in 2019, by estimation approach, as a share of all DALYs.
ATG: Antigua and Barbuda. FSM: Federated States of Micronesia. LCA: Saint Lucia. TLS: East Timor. TTO: Trinidad and Tobago.
VCT: Saint Vincent and the Grenadines.

Although economic losses do not represent an actual loss to GDP, a sense of the scale can be gained by expressing the economic consequences with respect to GDP. Figure 4 displays the economic burden of disease due to mental disorders under the three estimation approaches by GBD region, as a percent of regional GDP. (Estimates by absolute values per DALY are provided in Appendix 1, along with mapped data visualizing estimates across all values per DALY.) Across approaches, the greatest change in estimated burden occurs in Eastern Europe, Latin America, North America, and Southern sub-Saharan Africa. Under the relative GDP-per-capita values the economic burden would account for between 3.9% of gross domestic product in Eastern Sub-Saharan Africa and 7.9% in High-income North America under our composite approach.

1.4 Discussion

This study explores possible alternative approaches to estimating the global burden of mental illness and the economic losses thereof. In particular, we propose a composite approach to address contention in the classification of mental disorders. This approach suggests that the global DALYs attributable to mental disorders could exceed 418 million per year, or 16% of the total burden.

When applied against an economic value per DALY of one times GDP per capita, this approach further suggests that the per year losses associated with this burden could exceed 4.7 trillion USD in 2019. When adjusting for the uncertainty in estimates of the attributable burden of disease, the losses could range from 3.1 trillion to more than 6.9 trillion USD. Adjusting for purchasing power parity would increase the magnitude of these estimates, with ranges from 4.8 to 10.6 trillion international dollars at the global scale.

Put in context of the existing literature, our epidemiological and economic estimates provide two important contributions. First, our findings echo in magnitude those of Vigo and colleagues,²⁹ which have highlighted that suicide and premature mortality due to mental disorders are potentially

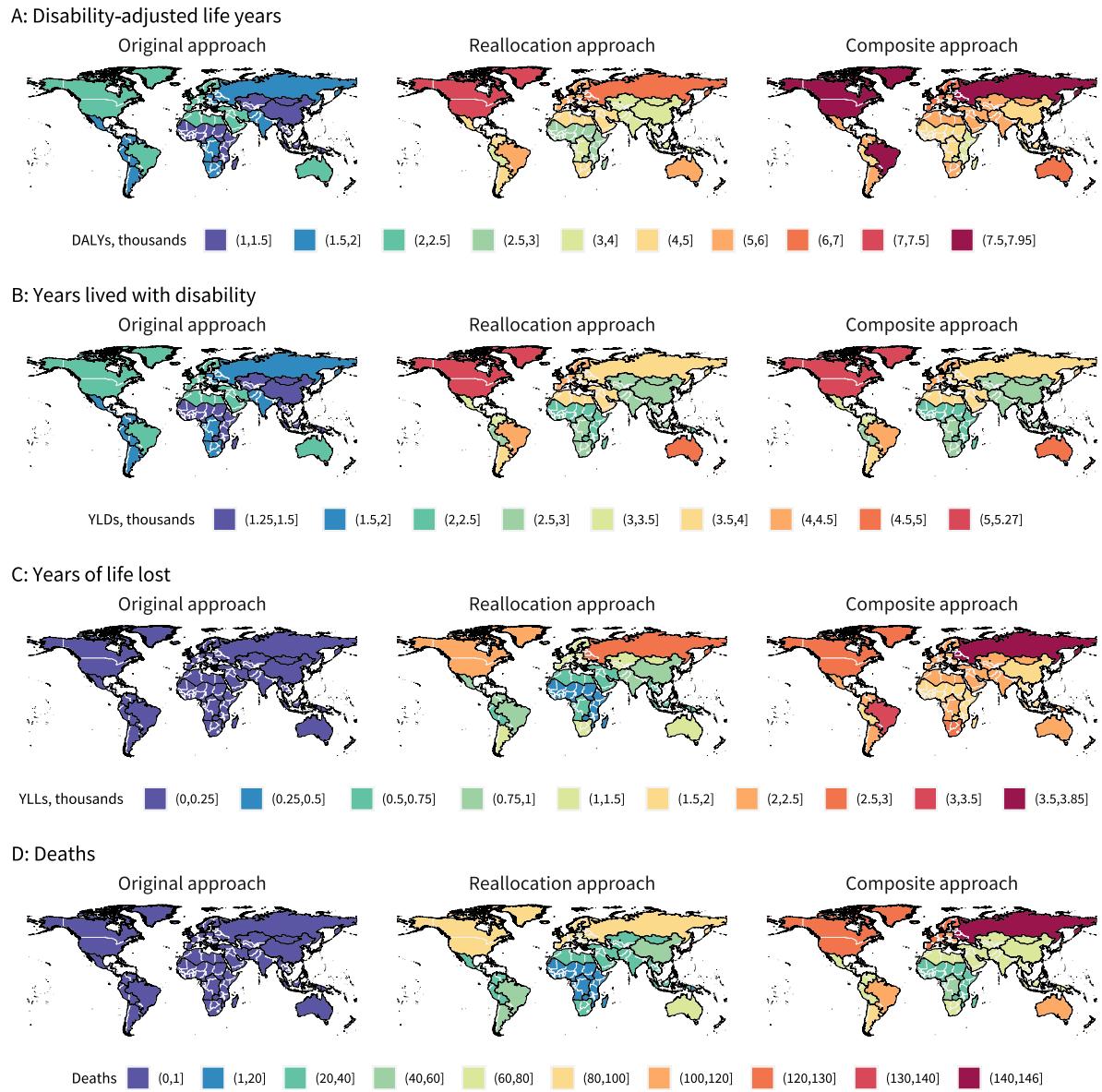


Figure 3: DALYs, YLDs, YLLs, and deaths attributable to mental disorders in 2019, by estimation approach, per 100,000 population. Values are aggregated by GBD region. DALYs: Disability-adjusted life years. YLDs: years lived with disability. YLLs: years of life lost. GBD: Global Burden of Disease.

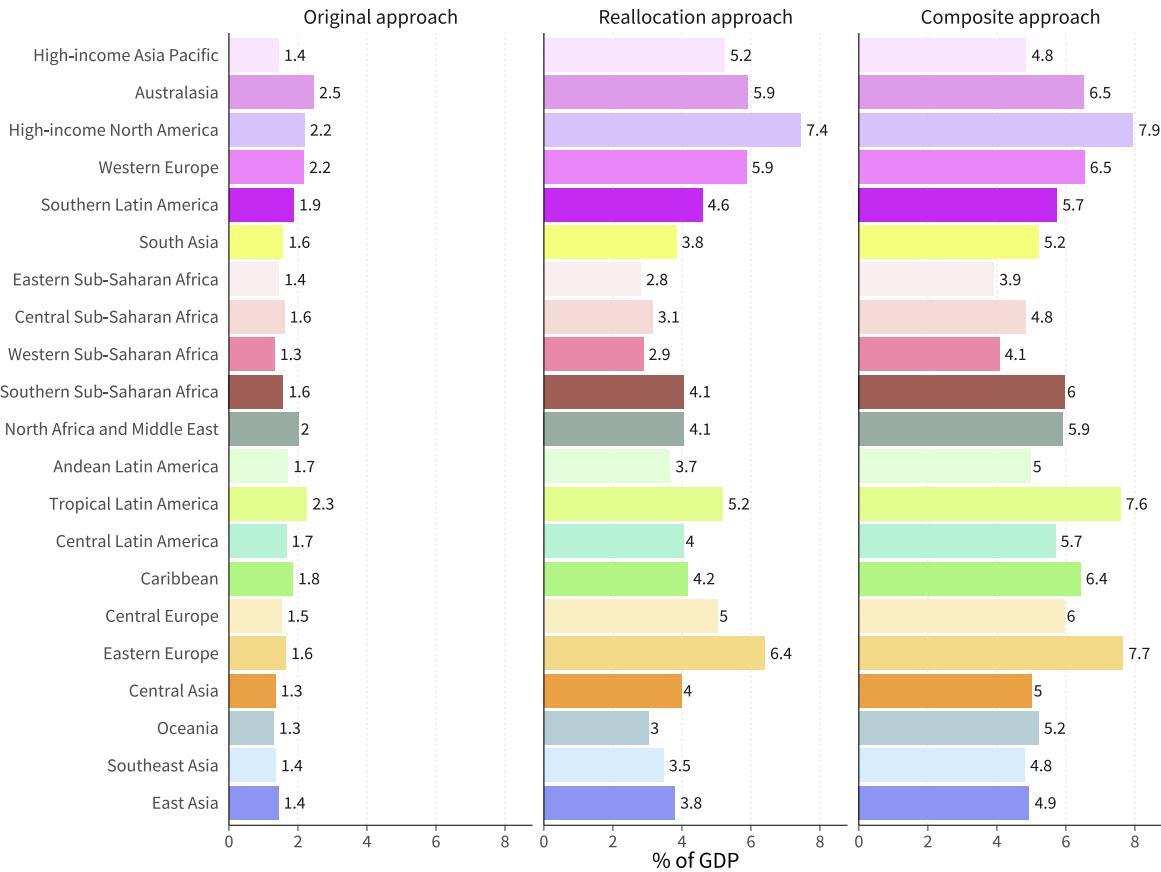


Figure 4: Economic burden of mental disorders, as a percent of GDP. The economic value is determined by using GDP per capita (USD 2019) as the value of a DALY. Values are aggregated by GBD region. GDP: gross domestic product. USD: United States dollar. DALY: disability-adjusted life year. GBD: Global Burden of Disease.

large sources of underestimation in the current GBD classification. Second, when including these sources of attributable mortality, the economic findings suggest staggering losses. We estimate that in 2019, the losses would already be over 1.8 trillion USD greater than Bloom and colleagues' global losses projections for 2030 (2.9 trillion 2019 USD, using the same value per DALY approach).²⁸

Our findings add to a growing literature concerning the classification of mental disorders, in particular related to underscoring the importance of including premature mortality attributable to mental disorders in burden conceptualizations.^{29,37,50,51} These calls have most recently been emphasized by GBD collaborators who have urged that "the differential mortality gap for individuals with mental disorders needs to be reflected within the GBD framework."³⁵ Our composite approach to assigning attributable mortality presents one potential attempt for acknowledging this differential mortality gap. Our economic analysis further provides updated monetary estimates of the burden of mental illness; to our knowledge, this is the first such analysis of the global economic burden of mental disorders in over a decade.

Our results should, however, be interpreted with several limitations in mind. First, our estimation approaches themselves all draw upon modeled data (i.e., GBD estimates). While GBD generates descriptions of morbidity and mortality at fine demographic and geographic levels, it is important to emphasize that the sophisticated modeling approaches implemented often draw on (potentially little) available underlying empirical data.⁵² These inputs can be extremely limited for particular diseases and geographical locations, especially so for mental disorders. By way of example, the GBD 2019 Data Input Sources Tool retrieves 3,084 separate data sources for mental disorders. Of these, only 60 pertain to sub-Saharan Africa (1.9%) and 58 to South Asia (1.8%).⁵³ By comparison, of the 6,064 records pertaining to maternal and neonatal disorders, 631 are for sub-Saharan Africa (10.4%) and 270 for South Asia (4.5%). These severely limited inputs reflect a dearth of global mental health data; as of 2017, the World Mental Health survey initiative had conducted interviews

in just 26 countries, only 13 of which were classified as low- or middle-income.²⁴

Relatedly, our composite approach relies on pooled estimates of the relative risk of mortality from a systematic review and meta-analysis that itself is limited by the available data it draws upon.⁵ The review identified 203 studies for inclusion, of which only two were located in Africa, 16 in Asia, and one in South America. While the authors found that the estimates of mortality risk did not vary by region, the limited representation of studies from the world's most populous and epidemiologically diverse continents is a considerable shortcoming. It is possible, for instance, that the relative risk of all-cause mortality associated with mental disorders is lower where the burden of mortality is more heavily concentrated among child, maternal, and infectious diseases, and is higher where the burden is dominated by NCDs. Therefore, to reach a conservative estimate of attributable mortality, we separately estimated population attributable fractions for natural and unnatural causes of death and restricted our allocation of YLLs from natural causes to NCDs—meaning no deaths from maternal or infectious diseases were attributed to mental disorders under the composite approach.

Furthermore, our composite approach allocates mortality due to mental disorders by calculating population attributable fractions using the conventional formula, which may be biased in the presence of confounding or effect heterogeneity.⁵⁴ In particular, the use of adjusted risk ratios (as in the current analysis) may result in anticonservative bias if the crude risk ratios are lower than the adjusted ones. To mitigate the potential for bias, our sensitivity analysis presents results under conservative assumptions for risk ratios and estimates of prevalence and mortality.

Despite these limitations, our findings underscore both that the true burden of mental disorders may only partially be captured by current estimation approaches, and that, consequently, the associated economic losses may be much higher than previously estimated. We note that our findings may themselves be an underestimate, as our composite approach excludes deaths due to

neonatal, maternal, and infectious diseases attributable to mental disorders. However, we observe that conventional estimation approaches may fail to capture large shares of premature mortality attributable to mental health causes, both from self-inflicted and unnatural causes of death and mortality from NCDs. Capturing this share of the burden emphasizes that mental health is a critical risk factor for premature mortality, as well as a direct source of morbidity.

The magnitude of economic costs associated with mental disorders raises the need for health economics research, particularly on returns on investment and costing for effective prevention and treatment strategies.⁵⁵ Further work is also needed to strengthen the measurement of the global burden of mental illness, not only for more fully capturing the morbidity and mortality of mental disorders, but also for incorporating the impacts of new and evolving threats—such as pandemics, conflicts and climate change—to population mental health.

Our study highlights that mental health—far from being an issue solely concentrated in high-income regions alone—is a major global issue, one that imposes a significant toll to health and welfare. The large magnitude of these twin burdens highlights the urgency for global action to support mental health financing and to bolster its prioritization.

1.5 Acknowledgements

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1.5.1 Author contributions

All authors contributed to study conception, methodology, and interpretation. DA oversaw data acquisition, programming, formal analysis, visualization, and the first draft of the manuscript. All

authors contributed to critical revision of the manuscript, with responses to reviewers and subsequent revisions led by DA.

1.5.2 Funding statement

This study received no funding.

1.5.3 Declaration of interests

We declare no competing interests.

1.5.4 Data sharing statement

GBD estimates are available for download from the Global Health Data Exchange and are available freely for non-commercial users under the Open Data Commons Attribution License (<https://ghdx.healthdata.org/gbd-2019>). All codes used for the analysis in this article are available on GitHub (https://github.com/darias5/gmh_econ).

2 Climate exposures and population mental health in Madagascar: an ecological study of national health information system data

Daniel Arias, Karestan Koenen, and Christopher Golden

Background: Climate change-related exposures (CCEs) are linked to worsened mental health, yet few studies of CCEs have taken place in low- and middle-income countries.

Methods: To better understand climate conditions and population mental health in these settings, we leverage meteorologic and geospatial data to explore the mental health impacts of three CCEs on monthly counts of patient visits for mental and neurological disorders reported by 3,413 facilities in Madagascar from 2010 to 2020. We used negative binomial regression to examine the impacts of three CCEs: temperature, soil moisture, and duration of cyclones and tropical storms.

Findings and interpretation: We found a statistically significant reduction in monthly visits reported associated with temperature—approximately 95.8% fewer visits reported per each degree Celsius increase (IRR: 0.958, p = 0.038, 99% CI: 0.909 – 1.010). A multiverse analysis of 192 models found this estimate to be robust to alternative specifications; ecoregion analysis indicated that this association was primarily localized to facilities in the central highlands, where cooler temperatures are more prevalent. We further found that higher soil moisture may be associated with higher mental health related visits in the future, with an 8.5% elevation in visits reported (IRR: 1.085, p < 0.0001, 99% CI: 1.046 – 1.127) after a three month lag. Ecoregion analysis suggests more visits are reported in the eastern lowlands and the northern dry deciduous forests when soil moisture rises, which is consistent with the geographic concentration of flood risk in Madagascar. Our findings highlight the complex interactions between CCEs and population mental health and suggest potential heterogeneity in how changing climate conditions will impact mental

health needs and system responses.

Keywords: climate mental health, planetary health, eco-anxiety, climate change, humidity, soil moisture, drought, temperature, cyclones.

2.1 Introduction

As empirical evidence increasingly highlights the wide-scale impact of human activities on climate, there is a growing, parallel body of evidence documenting the impacts our changing climate has on human health.⁵⁶ Rising temperatures and extreme weather events (including floods, hurricanes, droughts, and fires) have been associated with worsened health outcomes in multiple settings.^{57,58} In particular, these and other climate change-related exposures (CCEs) have been increasingly linked to worsened mental health⁶⁰, with systematic reviews suggesting, among other climate condition impacts, positive associations between high ambient temperatures and mental disorders,⁶¹ drought conditions and suicide,⁶² and cyclones and negative mental health outcomes.⁶³

Despite the weight of this evidence, few quantitative studies evaluating the effects of climate on population mental health have, to date, taken place in low- and middle-income countries (LMICs),⁶⁴ populations that—despite contributing the least to human-driven climate change—are among the most likely to be vulnerable to its impacts.⁶⁵

Among low-income countries most vulnerable to the health consequences of climate change is Madagascar, a nation that generates one percent *of* one percent of global carbon dioxide emissions. Worsening CCEs in Madagascar (primarily in the form of droughts, floods, and cyclones) are likely to exacerbate endemic, climate-sensitive threats to health, including malnutrition and malaria.⁶⁶ In particular, persistent drought conditions in recent years have led to extensive food insecurity.⁶⁷ Though there is debate concerning the extent to which human activity is directly responsible for Madagascar's current drought,^{68,69} the extremity of the situation has led some observers to classify

conditions in Madagascar as the first climate change famine in history.⁷⁰

Understanding how both incremental and extreme changes in climate impact population mental health is critical to gauging the full extent to which CCEs impact human health and well-being under a multidisciplinary approach to population health.⁷¹ This understanding is particularly important in contexts such as Madagascar, where climate conditions are already demonstrating pronounced pressures on economic, social, and physical well-being.

In investigating the impact of climate exposures on mental health, health system data can serve as a useful tool in settings where epidemiological survey data is sparse. Despite the poor availability of mental health services in many settings, routine health system data can still provide valuable insights into trends and patterns of service use and the need and distribution of care for mental health issues. Although these data may only capture a share of the true burden of disease, reported visits related to mental health complaints can be a valuable starting point for preliminary research into the impact of climate change on population mental health in resource-constrained settings.

In this ecological study, we investigated the association of climate conditions and population mental health in Madagascar between 2010 and 2020 using routine health system data from Madagascar's Ministry of Public Health. The use of health system data enabled us to indirectly evaluate the extent to which existing public health data may already be showing signals of CCEs, which may aid efforts to prevent and mitigate mental health stressors and better design systemic responses to mental health needs.

As a measure of population mental health, we considered facility-level monthly reported visits related to mental disorders; in terms of exposure, we explored the predictive association of three CCEs with incident mental health visits: mean monthly ambient air temperature, mean monthly soil moisture, and monthly cyclone activity. As exposure to these stressors could involve a delay in onset of mental health symptoms and subsequent care seeking, we further explored whether

exposures in prior months were associated with monthly reported visits in subsequent ones. We further considered interactive and additive models to account for complexity in the interaction of climate variables in Madagascar, as well as ecological variation to capture differences in regional climate systems.

2.2 Methods

2.2.1 Data

To analyze the impact of climate on population mental health in Madagascar, we first obtained health management information system (HMIS) data through a collaboration with the Madagascar Ministère de la Santé Publique. We then obtained gridded temperature and soil moisture data from the European ReAnalysis (ERA5)⁷² and the European Space Agency's Climate Change Initiative (ESA CCI),⁷³ respectively. Data on tropical storms and cyclones were obtained from open-source compilations of storms in the South-West Indian Ocean⁷⁴, which were in turn cross-referenced against storm trajectory data from the National Oceanic and Atmospheric Administration (NOAA)⁷⁵ for accuracy.

2.2.1.1 Outcomes Madagascar's health information system provided facility-level data on counts of disease incidence summarized and reported monthly. Prior to 2019, this system was the Gestion du Système d'Information Sanitaire (GESIS); in early 2019, the system transitioned to using District Health Information Software 2 (DHIS2).⁷⁶

Among facilities reporting any mental health data between 2010 and 2020, data were obtained from 3,204 public and private primary health centers (known as Centres Santé de Base or CSBs and Formations Sanitaires Privées de Base or FSBs, respectively), 164 district referral hospitals (CHDs), 45 regional referral hospitals (CHRRs) and university hospitals (CHUs), for a total of 3,413

uniquely-identified facilities in our sample.

Exploratory data analysis indicated that the classification and reporting of counts of mental disorders in GESIS varied across types of facilities in their level of detail. Among CHD facilities, incidence of mental disorders was aggregated with neurological disorders (coded as “neuro psychiatric disorders”), while CHRR and CHU facilities reported more detailed counts of specific mental disorders, such as depression, personality disorders, and schizophrenia. Across all facilities, disaggregated data was reported by age group but not by sex. Among CSB facilities, incidences of mental disorders were reported by age group under “mental illnesses and psychic disorders” until June 2015, when reporting was reclassified to “mental disorders,” and disaggregated data was reported by both age and sex. A summary of classification by facility type and year is provided in Appendix 2.1, Table S2.1, with English translations of the French disease names provided in Table S2.2. and yearly cumulative reported visit totals by disorder reported by facility level and year in Tables S2.3-5.

To address heterogeneity in reporting, our analysis aggregated any monthly visits concerning mental or neurological disorders reported by a facility, irrespective of age and sex, into a summary outcome measure. To address outliers, monthly observations of the outcome were arranged separately for each facility into a unique time series. The nonparametric Friedman’s super smoother regression estimator⁷⁷ was applied to each time series to identify outlier observations and replace them through linear interpolation.⁷⁸ By considering outliers on a facility-by-facility basis, the data cleaning approach preserved extreme values that may reflect true variances in incidence (for example, incidences reported by a large, regional reference hospital) while addressing potential errors in data entry. (Additional detail on the data cleaning process is available in Appendix 2.1)

2.2.1.2 Geospatial data To retrieve spatial climate data for the facilities in our sample, it was first necessary to geocode facilities to obtain their latitude and longitude. Facility data from

GESIS included limited geospatial information. While exact facility coordinates were not available, information on the relevant administrative unit served by a facility was included in the data (e.g., regions for CHRRs, districts for CHDs, and communes for CSBs). These data informed a stepwise matching process to locate facilities in our sample.

First, region, district, and commune names in our sample were standardized against reference shapefiles to address variations in translation, abbreviation, transposition, accent marks, spacing, hyphenation, and spelling. (A summary of the standardized names is provided in Appendix 2.2.) Next, facility names, types, and associated administrative units were used to match facilities to a validated spatial inventory of health facilities in Sub-Saharan Africa,⁷⁹ of which 2,625 coordinates were provided for public facilities in Madagascar. In order to systematically match facilities in our sample to facilities in the spatial inventory, we implemented approximate string matching, which allowed for facility names and administrative units to be matched approximately, rather than exactly, to corresponding patterns in the validated spatial inventory. Applying this matching technique, 1,768 facilities (52%) in our sample were matched to validated coordinates.

Among the remaining facilities, an additional 827 primary facilities were matched to coordinates from a spatial inventory of 3,171 coordinates obtained from the Routine Health Information Network (RHINO),⁸⁰ which supports an open source database of health facility data in conjunction with the United States Agency for International Development, the government of Madagascar, and other stakeholders.

To geolocate the remaining facilities, our existing inventories were combined with additional spatial inventories of health facility coordinates gathered from local consultants, the Global Healthsites Mapping Project, and other sources to create a database of 13,358 uniquely identified coordinates for potential matches. Using this database, an additional 448 facilities in our sample were geolocated using manual and approximate string matching.

An additional 255 facilities were matched to the centroid of their relevant administrative unit in cases where the unit was less than or equal to 225 square kilometers, as these administrative units are quite small relative to the spatial resolution of gridded climate data (approximately 900 km²). Among the remaining facilities, geolocations were manually identified for 115 facilities using targeted searches, resulting in 3,413 of the 3,413 facilities (100%) in the sample being geolocated.

To gauge the accuracy of the geolocating process, a subset of 1% of geolocated facilities was selected for validation against manually identified coordinates. Comparing the geolocated coordinates to validated coordinates for each facility, the mean distance between coordinates in the validation sample was 1.36 km, with a maximum distance of approximately 9.5 km, indicating high accuracy in the geolocated process relative to the spatial resolution of climate data. Additional detail on the geolocating and validation process is available in Appendix 2.2.

2.2.1.3 Climate data Facility geolocations were then used to retrieve spatially referenced monthly averages of temperature and soil moisture data from ERA5 and ESA CCI, respectively. To allow for modelling of lagged associations, data were obtained for both ERA5 and ESA CCI SM from January 2008 to July 2020.

ERA5 is a global atmospheric reanalysis from the European Centre for Medium-Range Weather Forecasts (ECMWF) and is freely available through its Copernicus Climate Change Service (C3S)⁷³. The spatial resolution of ERA5 is approximately 30 km, with quality-assured hourly estimates available from 1959 to the present.⁷³ Using Google Earth Engine, a time series of monthly aggregate values for mean air temperature in degrees Kelvin at a height of 2 meters was obtained for each facility geolocation.⁸¹ Temperature data was then converted to degrees Celsius.

We obtained soil moisture data from the European Space Agency's soil moisture dataset (ESA CCI SM), the world's first and most comprehensive, multi-decade, satellite-observed dataset of global

soil moisture. The spatial resolution of ESA CCI SM is approximately 26 km, with daily estimates available from 1978 to 2021. Using ESA CCI SM active and passive radiometer data, a time series of monthly aggregate values for mean soil moisture—measured as saturation percentage—was constructed from daily observations at each land grid point within Madagascar. We then applied nearest neighbor matching to link these time series to our geolocated facilities.

For a location to have soil moisture data available in ESA CCI SM, it must fall within one of 244,243 land grid points. For some facilities on Madagascar’s coastline, their location placed them outside of ESA CCI’s spatial coverage, resulting in missing values. To address facilities without any soil moisture data, nearest neighbor searching was conducted to identify the nearest land grid point for which ESA CCI SM data would be available; this nearest neighbor’s soil moisture time series data would then be applied to the facility with missing data. Within a time series of ESA CCI data for a given location, however, monthly data could still be missing if adequate satellite observation was not recorded anytime during a given month; for these values, we used linear interpolation to address missing data within a time series.

In addition, we obtained data on tropical storms and cyclones in the South-West Indian Ocean for the 2009-2010 to 2020-2021 seasons, inclusive. Open source data on tropical cyclones in the south-west Indian Ocean was obtained by scraping information from Wikipedia summaries of each cyclone season, which were originally sourced from alerts issued by Météo-France La Réunion (MFR La Réunion), the World Meteorological Organisation designated Regional Specialized Meteorological Centre (RSMC) for the provision of forecasts and warnings of tropical cyclones in the South-West Indian Ocean. To ensure that the compiled data accurately reflected storms in Madagascar during the study period, we cross-referenced these data against storm trajectory data for the South Indian Basin from NOAA.⁷⁵

With these data, we generated two indicators to measure exposure to storm activity in a given

month: a binary indicator for whether a storm impacted Madagascar in that month and a count indicator for the number of days per month with a storm. To capture lingering post-dissipation effects, we defined impact as the storm's duration plus an additional 14 days.

2.2.2 Statistical analysis

All analyses were completed using R (version 4.2.1).⁴⁹ Marginal effects were calculated using the ‘margins’ package (version 0.3.26)⁸² for R.

2.2.2.1 Modeling approach Exploratory data analysis highlighted that the variance of monthly facility-level counts of incident mental disorders highly exceeded the mean; consequently, our statistical analysis utilized negative binomial (NB) regression, which is recommended in the case of over-dispersed count data.

Our primary analysis involved conducting four models to estimate the association between facility-level counts of incident mental disorders and climate conditions. Model 1 used temperature as the principal predictor of counts of incident mental disorders. Model 2 only used soil moisture as a predictor. Model 3 used both temperature and soil moisture independently as predictors, while Model 4—our preferred model—introduced an interaction term between the two.

Duration of cyclone activity was included in all models using our count indicator of exposure. In all models, we included fixed effects for Madagascar’s twenty-two regions to account for geographic differences in climate patterns and case/visit reporting. We further included month and year fixed effects to account for seasonality and time-varying omitted variables.

In addition, to aid in the interpretation of results, our analysis further reported the average marginal effect of each model predictor. Marginal effects clarify the effect of a per-unit change in a continuous explanatory variable (e.g., temperature) on an outcome where the regression model involves interaction. (In models without interaction or higher-order terms, the slope coefficient from

the model will equal the marginal effect.) In addition to estimating the average marginal effects of our temperature, soil moisture, and cyclone variables, we further calculated the marginal effect and predicted values of the outcome for each unit of climate exposure across the three variables of interest.

Though CCEs could acutely impact mental health in our sample, we could anticipate that these impacts might not immediately result in changes to monthly case and visit counts, owing to delays in symptom onset, care seeking, and care delivery. To test for lagged associations—that is, whether in a given month, climate conditions in prior months were associated with counts of mental disorders—versions of Model 4 were conducted using lagged predictors. Measures of association were estimated for each monthly lag increment between 1 month and 18 months, inclusive.

Owing to the large number of observations in our sample, significance was evaluated against an alpha of 0.01, with 99% confidence intervals reported. Coefficients and confidence intervals for our indicators of climate exposure were exponentiated to generated incidence rate ratios (IRRs). Confidence intervals were constructed using heteroskedasticity-robust standard errors.

2.2.2.2 Subgroup analysis Madagascar is home to a diverse range of terrestrial ecoregions, each of which has unique physical, climatic, and ecological characteristics. These variations in the environment include distinct patterns of rainfall, temperature, and cyclone activity, potentially resulting in effect heterogeneity when examining how these exposures impact human health across different ecoregions.

To explore potential heterogeneity of our effect estimates, we evaluated Models 1 through 4 among facilities in each of Madagascar's four predominant ecoregions: the lowland, humid forests of the east, the subhumid forests of the Central High Plateau, the desert and xeric shrublands of the south, and the northeastern Dry deciduous forests. (Ecoregions are presented in Figure 5.)

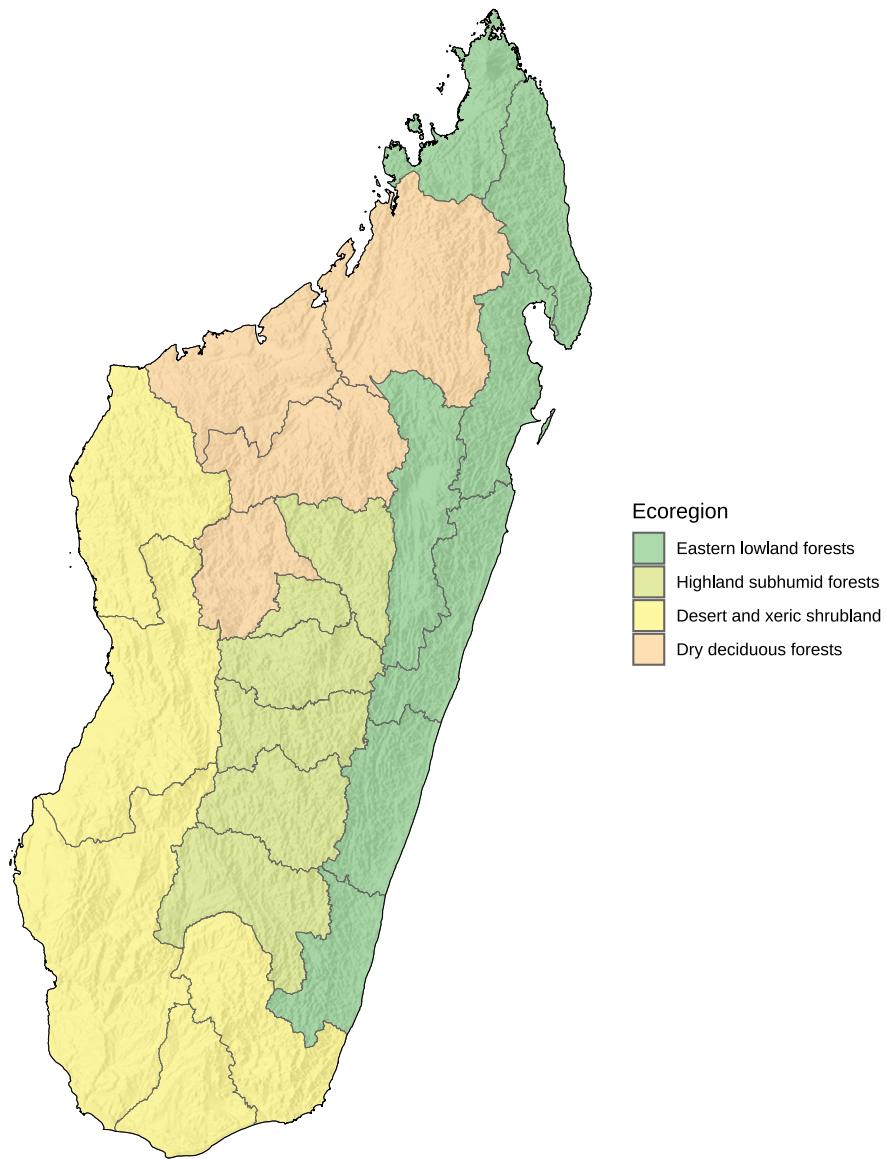


Figure 5: Predominant ecoregions of Madagascar, summarized by administrative region.

2.2.2.3 Sensitivity analysis In order to evaluate the robustness of our main results to alternative specifications, data processing, and modeling decisions, we generated 192 plausible model combinations to conduct a multiverse analysis to identify how sensitive effect estimates and confidence intervals were to different methodological choices.

To generate the model combinations, we first detailed seven methodological choices and their potential specifications. These criteria are outlined in Table 2.1.

Table 2.1: Alternative specifications, data processing, and modeling decisions for multiverse analysis.

*: preferred specification. CSB/FSP: Centres Santé de Base and Formations Sanitaires Privées de Base. NB: negative binomial model

1. Data cleaning for outcome data
a) Linear interpolation to replace outliers *
b) No adjustment (raw data)
2. Sample
a) Full sample *
b) Primary care facilities only (CSB/FSP)
3. Relationship of temperature and soil moisture
a) Additive model
b) Interactive model *
4. Regression framework
a) NB model *
b) Poisson model
5. Cyclone activity
a) Count indicator
b) Binary indicator
c) Excluded (i.e., no indicator)
6. Month and year fixed effects
a) Included *
b) Excluded
7. Regional fixed effects
a) Included *
b) Excluded

First, we considered the role of data cleaning in the outcome data and chose to compare our analysis using the cleaned outcome data against the raw, unadjusted values. Second, we chose to compare our findings using data from all facilities (the full sample) against a sample without district and regional hospital (CSB/FSP facilities only). Primary care facilities have smaller catchment areas than hospitals; consequently, it is more plausible that climate data for primary care facilities will closely reflect climate exposure to patients compared to referral hospitals. Third, we considered the decision to model temperature and soil moisture as an additive or interactive relationship (Model 3 vs. Model 4), with both alternatives included in our multiverse analysis. Fourth, we evaluated our decision to account for overdispersion with a NB model by using a Poisson regression framework as an alternative. Fifth, we evaluated alternative specifications of exposure to cyclone activity, using three options: our binary indicator, our count indicator, and no term for cyclone activity included. Sixth, we varied whether time fixed effects (month and year) were included. Seventh, we similarly included and excluded regional fixed effects for comparison.

We then interacted the methodological choices to generate 192 plausible models. Using the effect estimates and confidence intervals for these models, we constructed specification curves for monthly temperature, soil moisture, and—for the 64 models that included the cyclone count indicator—cyclone activity to visually compare the distribution of plausible estimates under different combinations.

2.2.2.4 Ethics statement The Institutional Review Board (IRB) of the Harvard T.H. Chan School of Public Health determined that this study was not human subjects research and that additional review was not required (protocol number: IRB21-1303, determined on October 19, 2021).

2.3 Results

Our geolocated sample of facilities—which is displayed in Figure 6—showed geographic diversity and comprehensive coverage across Madagascar, with most geolocations identified through validated sources.

Figure 7 shows the spatial distribution of temperature and soil moisture across the facilities in our sample during January and June 2015, corresponding to the warmer, wet season and the dryer, cool season, respectively. When evaluated over time, annual climate trends in Madagascar showed relatively stable distribution of average temperatures, while soil moisture had a slight upward shift through 2020 (Figure 8). Data of tropical storm and cyclone activity throughout the study period also exhibited seasonal patterns, with most major storms occurring in the hot season, with a peak between February and May (Figure 9).

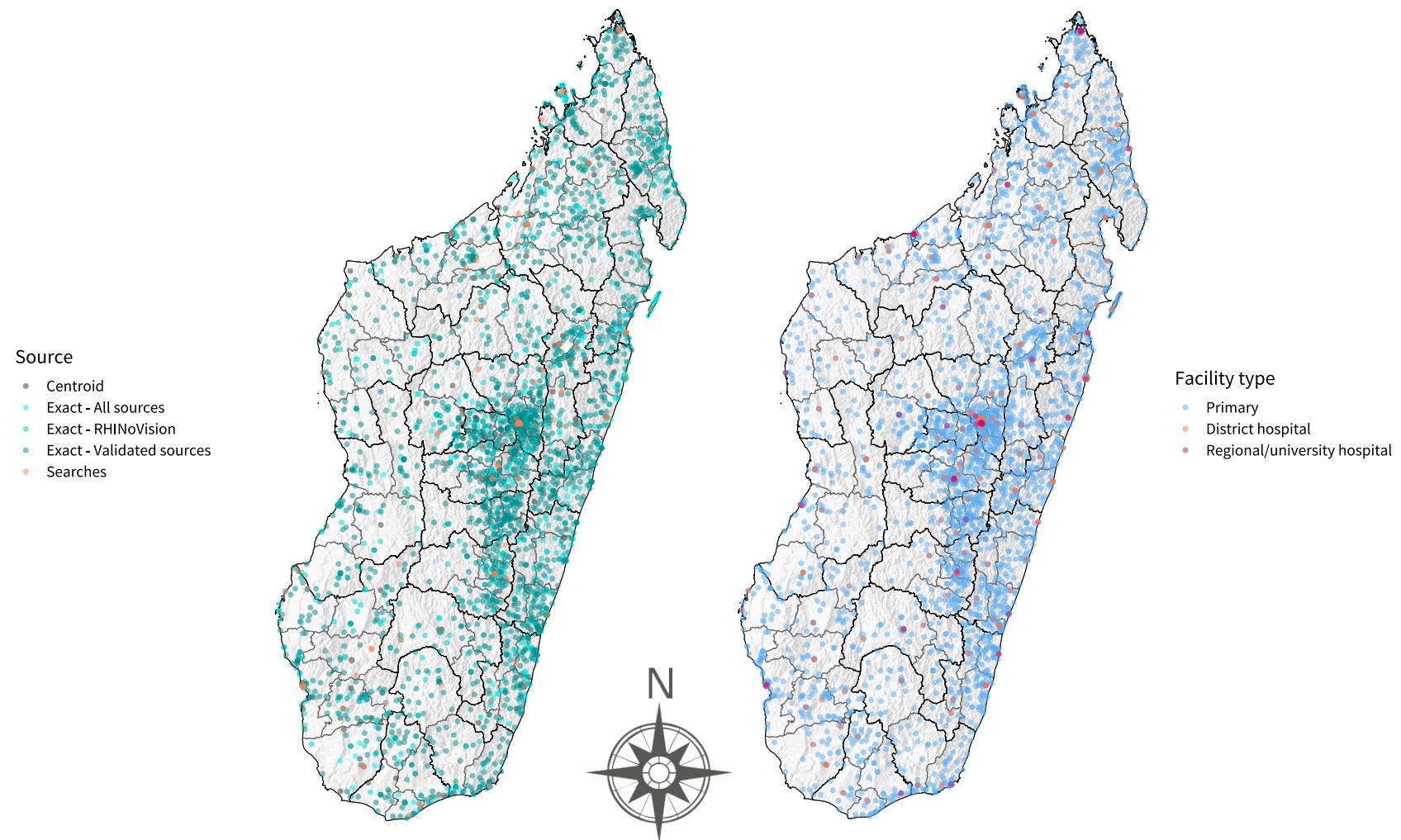


Figure 6: Map of facilities in Madagascar, by coordinate source (left panel) and facility type (right panel).

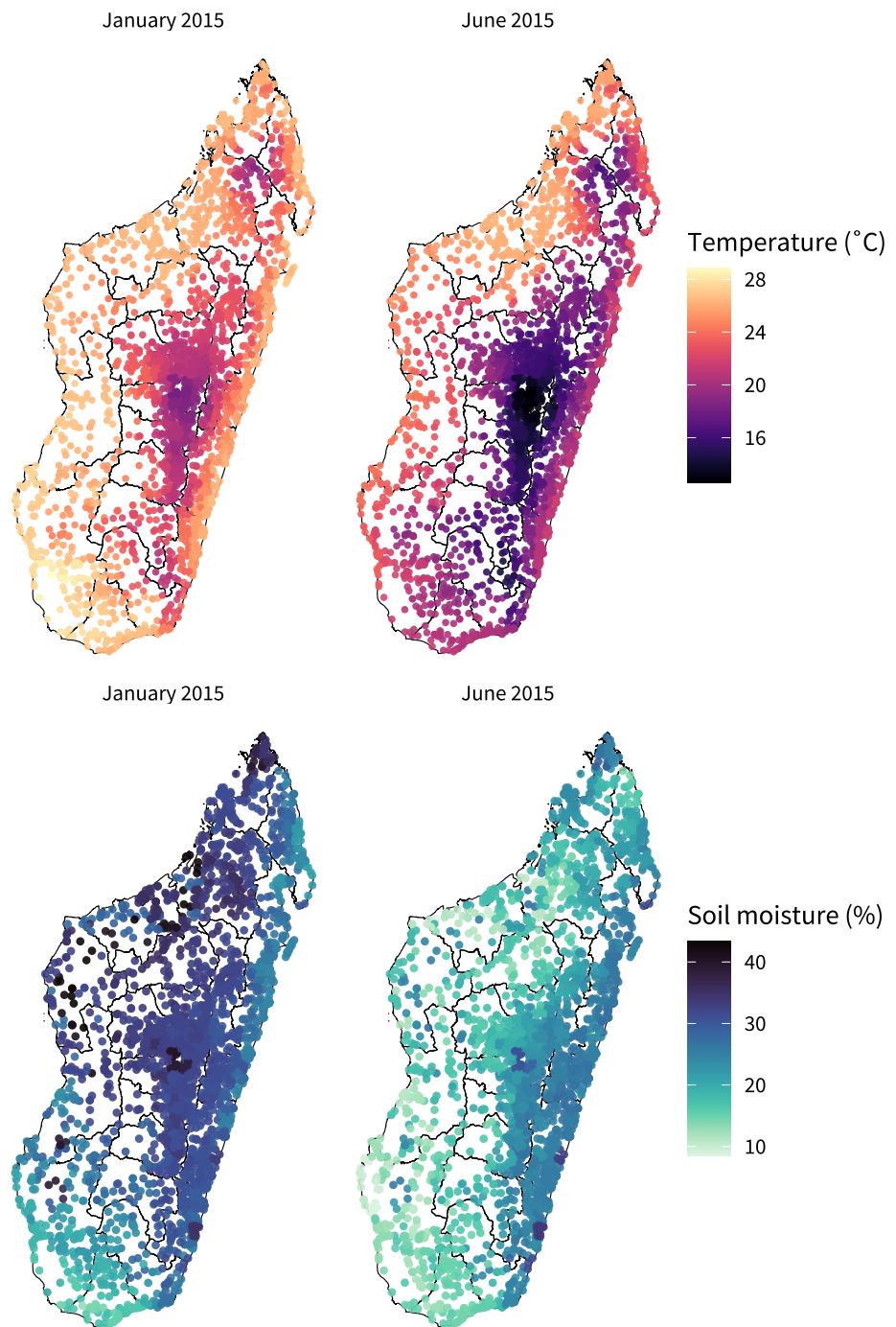


Figure 7: Spatial distribution of climate conditions across clinics and seasons in Madagascar. Mean monthly temperature (top) is measured in degrees Celcius and mean soil moisture is measured in percent saturation (below).

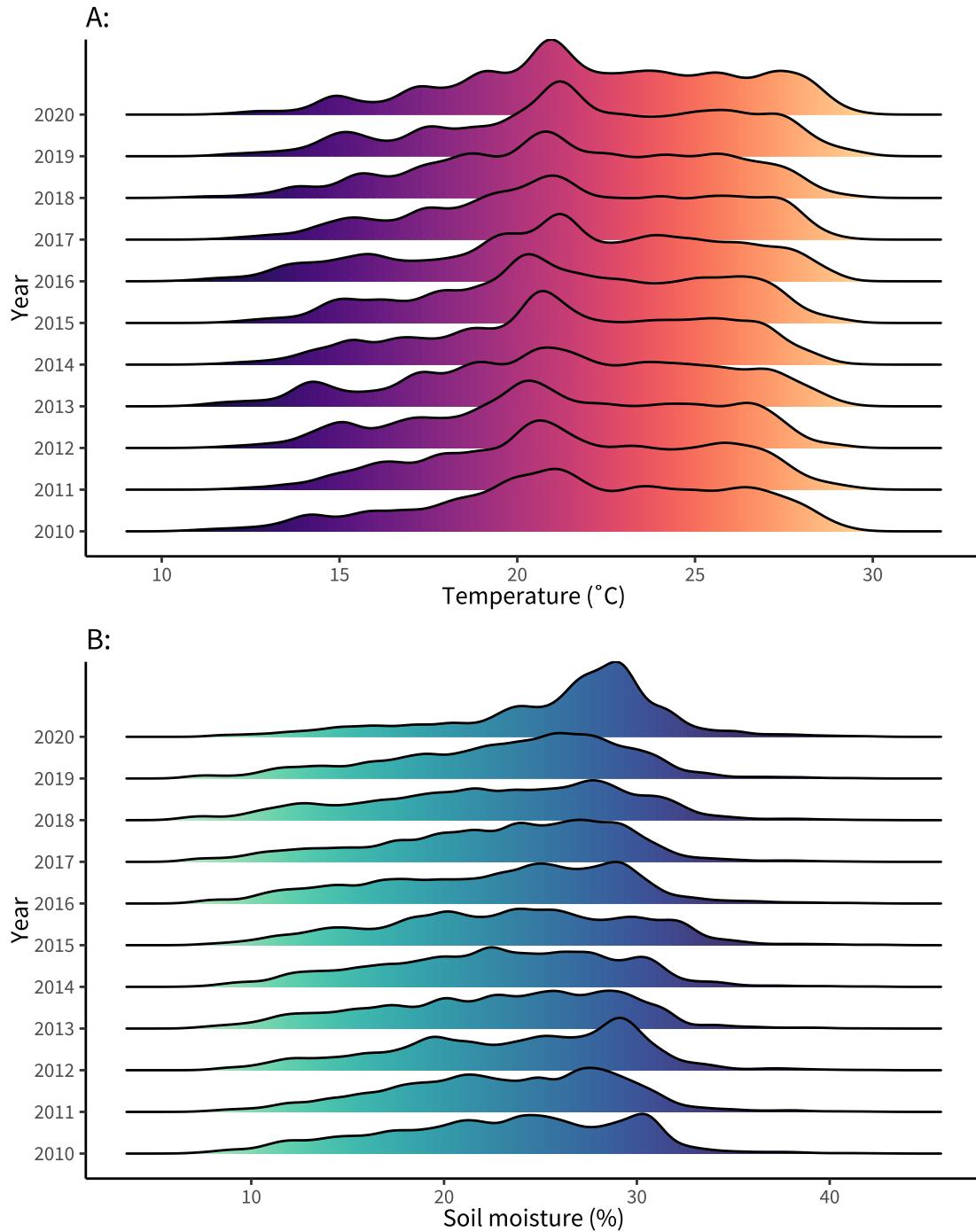


Figure 8: Distribution of A) temperature and B) soil moisture across all month-years and all clinics.

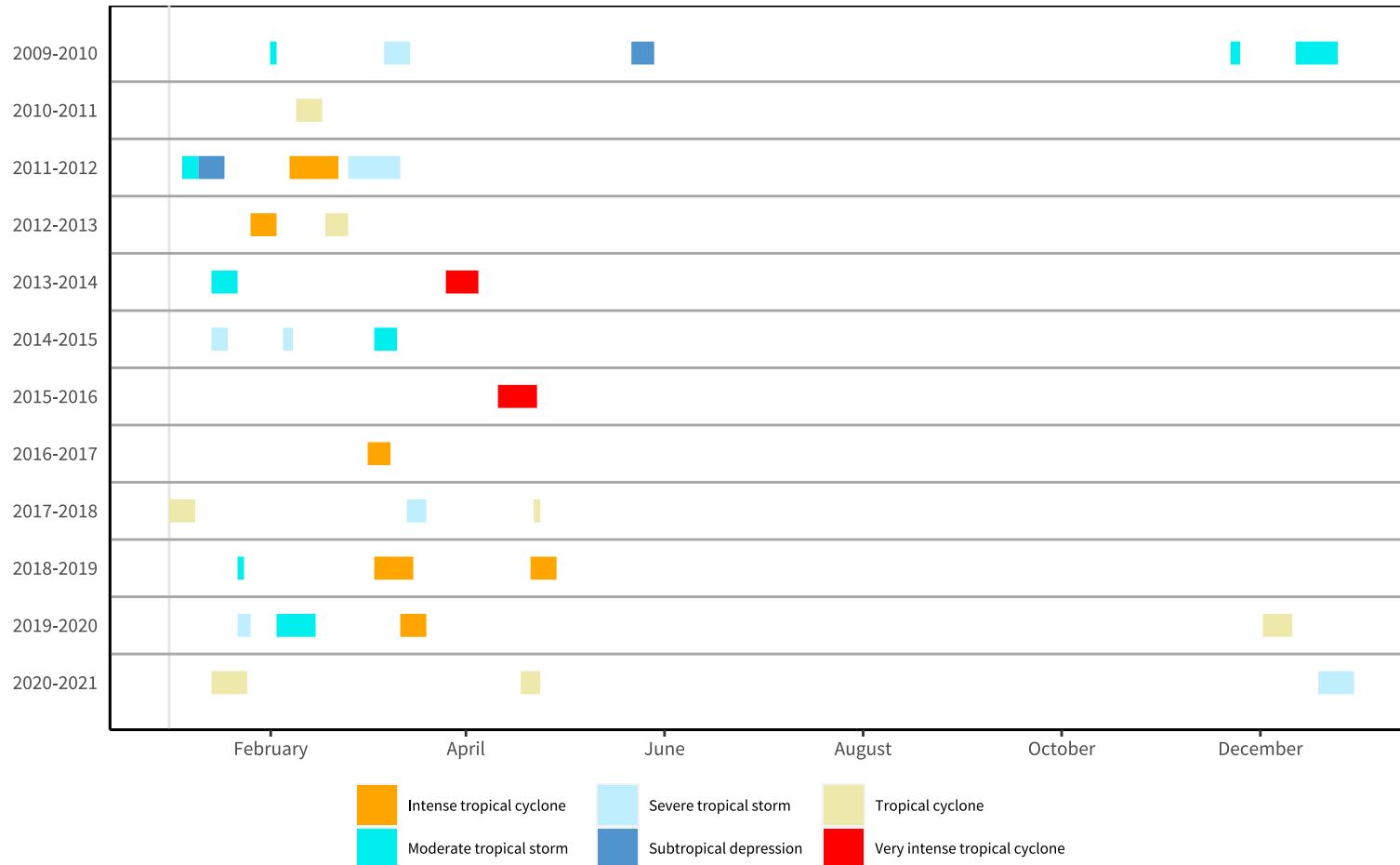


Figure 9: Tropical storms and cyclones in Madagascar by intensity and season, 2009-2010 to 2020-2021, inclusive.

Table 2.2: incidence rate ratios (IRRs) and average marginal effects (AME) of climate exposures on monthly reported visits related to mental and neurological disorders, Models 1 through 4.

	IRR (99% CI)	M.E. (99% CI)
<hr/>		
Model 1 ^{a,b}		
Temperature	0.954 (0.934 – 0.973)***	-2.26 (-3.3 – -1.23)***
Cyclone (count)	0.995 (0.987 – 1)	-0.248 (-0.536 – 0.04)*
<hr/>		
Model 2 ^{a,b}		
Soil moisture	0.999 (0.985 – 1.01)	-0.0677 (-0.574 – 0.438)
Cyclone (count)	0.995 (0.987 – 1)	-0.264 (-0.559 – 0.0311)*
<hr/>		
Model 3 ^{a,b}		
Temperature	0.944 (0.923 – 0.965)***	-2.77 (-3.88 – -1.65)***
Soil moisture	0.991 (0.976 – 1.01)	-0.454 (-0.986 – 0.0782)*
Cyclone (count)	0.994 (0.986 – 1)*	-0.296 (-0.59 – -0.00168)**
<hr/>		
Model 4 ^{a,b}		
Temperature	0.958 (0.909 – 1.01)*	-2.85 (-3.98 – -1.72)***
Soil moisture	1.01 (0.958 – 1.06)	-0.354 (-0.966 – 0.258)
Temperature X Soil moisture	0.999 (0.997 – 1)	
Cyclone (count)	0.994 (0.986 – 1)*	-0.3 (-0.595 – -0.0055)**

^aModel 1: Temperature only. Model 2: Soil moisture only. Model 3: Temperature and soil moisture, additive model. Model 4: Temperature and soil moisture, interactive model. All models include a count indicator for days of exposure to cyclone activity, as well as month, year, and regional fixed effects.

^b*** p < 0.001, ** p < 0.01, * p < 0.05

{1.5}

2.3.1 Main analysis

The regression models predicting monthly counts of any mental or neurological disorder (Table 2.2) showed significant associations with temperature across all models. A one-degree Celsius increase in temperature was associated with approximately 95.4% fewer visits reported (IRR: 0.954, p < 0.0001, 99% CI: 0.934 – 0.973) by primary clinics and hospitals in Model 1. Inclusion of both climate predictors resulted in little change to the measure of association for temperature. In an additive model with soil moisture included (Model 3), the effect estimate associated with temperature grew to 94.4% fewer visits reported (IRR: 0.944, p < 0.0001, 99% CI: 0.923 – 0.965). Adopting an interactive model (Model 4) attenuated the association (IRR: 0.958, p = 0.038, 99% CI: 0.909 – 1.010), but remained significant at a 95% level of confidence. Across all models with temperature, the average marginal effect associated with temperature (across a sample with all clinics) ranged between 2 and 3 fewer monthly mental health visits reported and was statistically significant at an alpha of 0.01, with the average marginal effect in Model 4 being -2.848 visits (p < 0.001, 99% CI: -3.976 – -1.719).

Effect estimates associated with soil moisture were not statistically significant across all four models. In all models, we observed a modest reduction in visits reported per each additional day duration of cyclone activity, with the incidence ratio ratios of Models 3 (IRR: 0.994, p = 0.047, 99% CI: 0.986 – 1.002) and Models 4 (IRR: 0.994, p = 0.047, 99% CI: 0.986 – 1.002) being significant at a level of 0.05. In all models, however, the average marginal effect was close to 0, with the average marginal effect in Model 4 being only -0.300 visits (p = 0.009, 99% CI: -0.595 – -0.006).

Predicted values of monthly mental health related visits counts under Model 4 echoed the effect estimates from Table 2, with fewer visits reported in warmer months (Figure 10). Marginal effect estimates across the distribution of temperatures in our data showed that the greatest level of reduction occurred between 10 and 15 degrees Celsius, with each degree increase associated with 4

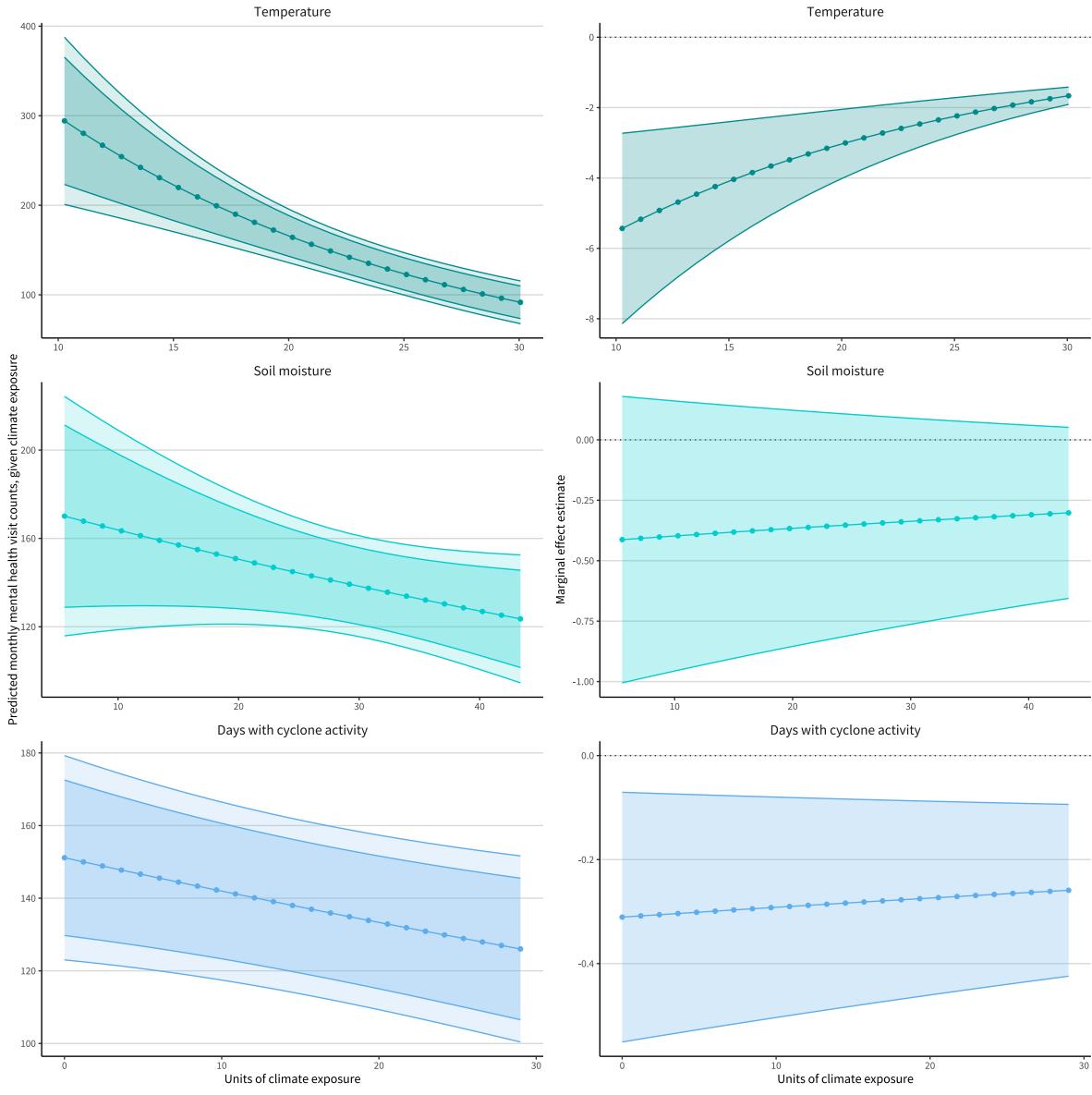


Figure 10: Predicted values of monthly mental health visits and marginal effect estimates by coefficient and their 95% and 99% confidence intervals. The left panels show predicted values of monthly counts of visits related to mental and neurological disorders in Madagascar, given different units of climate exposure. The right panels show marginal effect estimates over different units of climate exposure in the data. The dotted horizontal lines in the right panel depict no marginal effect on visit counts. In all panels, the model used to generate predictions and marginal effects corresponds to Model 4. Units of climate exposure are degrees Celsius for temperature (top), saturation percentage for soil moisture (middle), and days with cyclone activity (bottom).

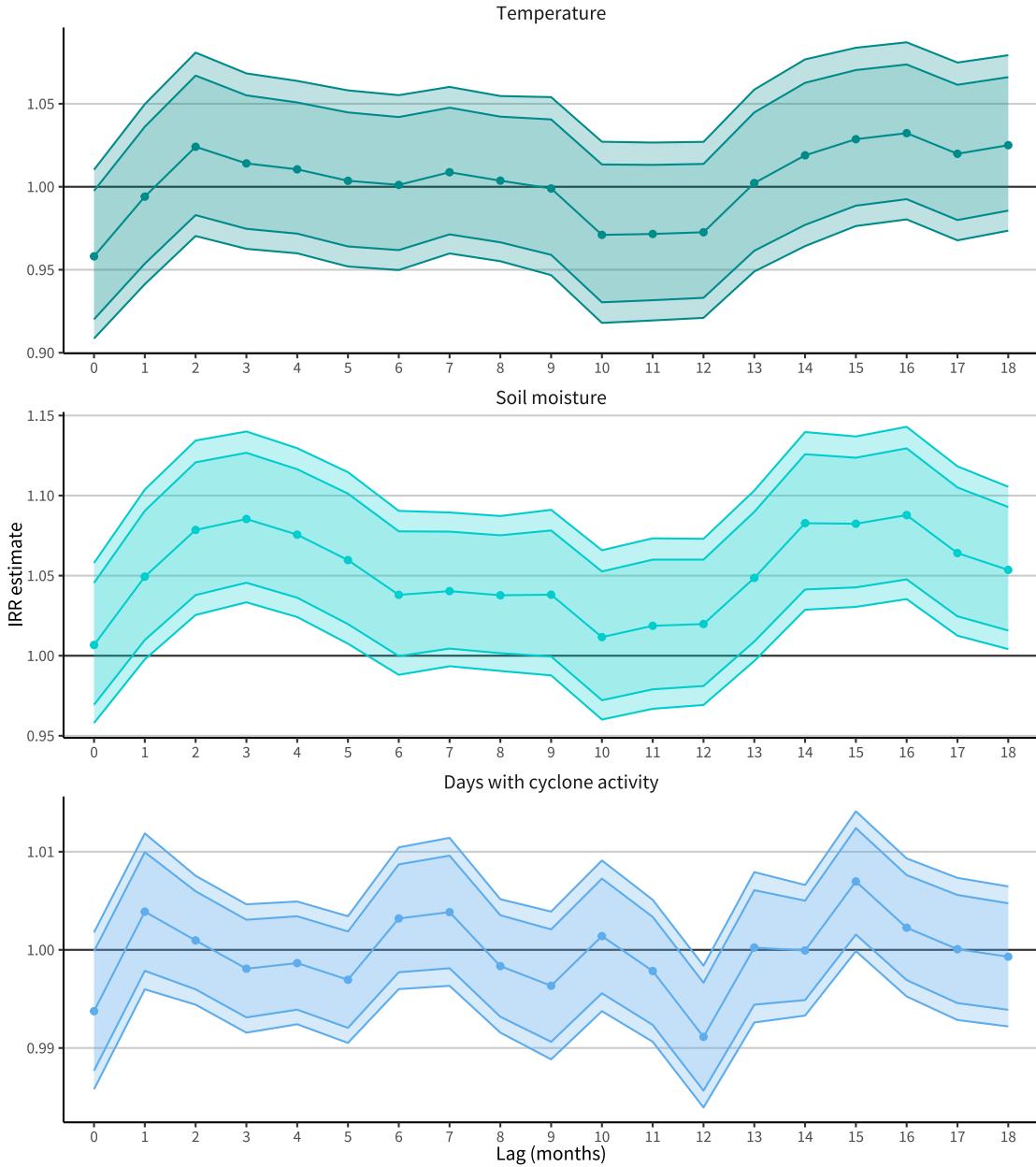


Figure 11: Effect estimates by coefficient with lagged exposures and their 95% and 99% confidence intervals, Model 4. The x-axis correspond to the length of the lag (e.g., a value of 2 reflects a lag of two months, such that visit counts are predicted by climate conditions two months prior), with the value of 0 reflecting a model without any lag in exposure. The dotted horizontal lines depict a null effect. IRR: incidence rate ratio.

to 5 fewer visits related to mental or neurological disorders reported, controlling for other covariates. Months with greater levels of soil moisture and days with cyclone activity also showed fewer reported visits; however, the marginal effects associated with soil moisture were not significant across any unit of exposure, while those associated with days with cyclone activity were close to zero for all lengths of activity.

Examining lagged effects showed potential temporal associations between soil moisture levels in preceding months and visit counts in those following (Figure 11), with higher saturation leading to a statistically significant elevation in visits reported 1 to 5 months later. At a lag of 3 months, the elevation in visits was approximately 8.5% (IRR: 1.085, $p < 0.0001$, 99% CI: 1.046 – 1.127). There appeared to be a significant elevation of similar magnitude 13 to 17 months prior, suggesting potential annularity in lagged association. Effects for temperature were not significant across any lag; cyclone activity similarly showed no significance in lags under a year, but did show modest, statistically significant associations at lags of 12 months (IRR: 0.991, $p = 0.002$, 99% CI: 0.986 – 0.997) and 15 months (IRR: 1.007, $p = 0.011$, 99% CI: 1.002 – 1.012). A slight increase in visits was associated with cyclone activity in a prior month, but this increase was not statistically significant (IRR: 1.004, $p = 0.206$, 99% CI: 0.998 – 1.010).

2.3.2 Subgroup analysis

Results from our subgroup analysis showed evidence of potential effect heterogeneity by ecoregion (Table 2.3). For temperature, estimates of association were only statistically significant in the highland subhumid forests, where each one-degree Celsius increase in temperature was associated with 74.8% fewer visits reported (IRR: 0.748, $p < 0.0001$, 99% CI: 0.632 – 0.885). Temperature was associated with a slight increase in visits in the eastern lowland forests (IRR: 1.016, $p = 0.785$, 99% CI: 0.875 – 1.180) and the desert and xeric shrublands (IRR: 1.016, $p = 0.785$, 99% CI: 0.875 –

1.180), but in neither case was the estimate significant at a level of 0.05.

Table 2.3: subgroup analysis results, summarized by incidence rate ratios (IRRs) and average marginal effects (AME) from Models 1 through 4.

	IRR (99% CI)	M.E. (99% CI)
Temperature ^{a,b}		
All	0.958 (0.909 – 1.01)*	-2.85 (-3.98 – -1.72)***
Eastern lowland forests	1.02 (0.875 – 1.18)	-0.525 (-1.84 – 0.795)
Highland subhumid forests	0.748 (0.632 – 0.885)***	-17 (-21.5 – -12.4)***
Desert and xeric shrubland	1.02 (0.847 – 1.23)	0.898 (-0.716 – 2.51)
Dry deciduous forests	1 (0.9 – 1.11)	-2.67 (-4.24 – -1.11)***
Soil moisture ^{a,b}		
All	1.01 (0.958 – 1.06)	-0.354 (-0.966 – 0.258)
Eastern lowland forests	1.11 (0.966 – 1.27)	2.77 (1.8 – 3.74)***
Highland subhumid forests	0.859 (0.754 – 0.979)**	-7.18 (-9.53 – -4.83)***
Desert and xeric shrubland	0.872 (0.688 – 1.11)	-1.69 (-2.25 – -1.13)***
Dry deciduous forests	1.22 (1.08 – 1.37)***	3.49 (2.35 – 4.63)***
Temperature X Soil moisture ^{a,b}		
All	0.999 (0.997 – 1)	
Eastern lowland forests	0.999 (0.993 – 1)	
Highland subhumid forests	1 (0.996 – 1.01)	
Desert and xeric shrubland	1 (0.992 – 1.01)	
Dry deciduous forests	0.996 (0.992 – 1)*	
Cyclone (count) ^{a,b}		
All	0.994 (0.986 – 1)*	-0.3 (-0.595 – -0.0055)**
Eastern lowland forests	0.992 (0.981 – 1)	-0.288 (-0.69 – 0.115)
Highland subhumid forests	0.997 (0.985 – 1.01)	-0.248 (-1.05 – 0.549)
Desert and xeric shrubland	0.999 (0.979 – 1.02)	-0.0146 (-0.317 – 0.288)
Dry deciduous forests	0.986 (0.971 – 1)*	-0.457 (-0.951 – 0.0362)*

^aEstimates from Model 4 (interactive model), which include month, year, and regional fixed effects.

^{b***} p < 0.001, ** p < 0.01, * p < 0.05

With respect to soil moisture, while our primary analysis found no evidence of a statistically significant association with reported visits in the full sample, we found evidence of heterogeneity in our subgroup analysis. Among facilities in the highland subhumid forests, we found that each percentage point increase in soil moisture was associated with 85.9% fewer reported visits (IRR: 0.859, p = 0.003, 99% CI: 0.754 – 0.979), with an average marginal effect of -7.178 reported visits (p < 0.001, 99% CI: -9.527 – -4.830). Conversely, each percentage point increase in soil moisture in the dry deciduous forests was associated with a 21.6% increase in reported visits (IRR: 1.216, p < 0.0001, 99% CI: 1.077 – 1.373), with an average marginal effect of 3.490 reported visits (p < 0.001, 99% CI: 2.350 – 4.631).

Finally, our estimates of the incidence rate ratio associated with each additional day of cyclone duration in a given month were consistent between each ecoregion and our full sample. Among facilities in the dry deciduous forests, each additional day of cyclone activity was associated with the greatest reduction in reported visits (IRR: 0.986, p = 0.016, 99% CI: 0.971 – 1.001).

2.3.3 Multiverse analysis

In our multiverse analysis, 157 of 192 models (82%) returned effect estimates for temperature associating a one-degree increase with fewer reported visits related to mental or neurological disorders, with 115 (60%) of those estimates having p-values below 0.01 (Figure 12). Only 6 (3%) models returned statistically significant IRR estimates greater than 1; all six models were negative binomial interactive models that excluded month and year fixed effects and were run on data that restricted to the CSB/FSP sample only.

With respect to soil moisture, only 65 of 192 models (34%) returned effect estimates with p-values below 0.01, with 40 of such models reporting IRRs greater than 1 and 25 models reporting IRRs

smaller than 1 (Figure 13). The overwhelming majority of models showed no significant association between soil moisture and monthly visit counts, in either direction. Of models showing statistically significant IRRs of a magnitude greater than 1, all excluded both region and time fixed effects.

Among the 64 models that included cyclone activity measured in days per month, 58 models (91%) reported reduced visit counts associated with cyclone duration, compared to 6 models (9%) showing IRRs below 1 (Figure 14). None of the 64 models, however, had a p-value below 0.01.

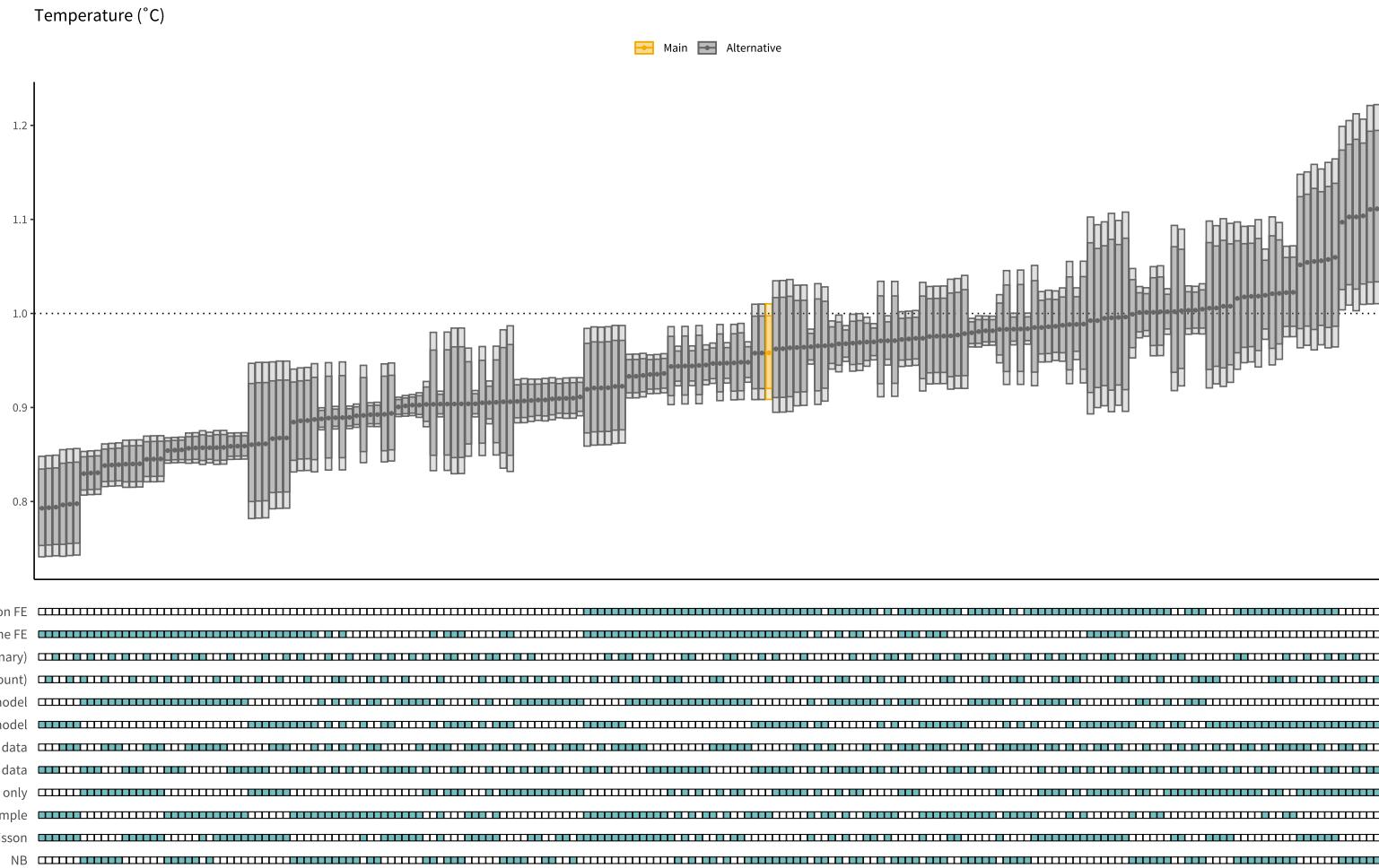


Figure 12: Specification curve depicting the effect estimates and confidence intervals for mean monthly temperature (degrees Celsius) across 192 models. In the top panel, estimated incidence rate ratios (IRRs) across different models are depicted as circles; the darkly and lightly shaded regions above and below these circles correspond to 95% and 99% confidence intervals of these estimates, respectively. The dotted horizontal line depicts a null effect. The IRR estimate and confidence intervals of the preferred model, Model 4, are highlighted in orange. Below each model, a legend of shaded and unshaded boxes indicates which modeling decisions correspond to a given model, with boxes shaded teal showing active features. FE: fixed effects. CSB/FSP: Centres Santé de Base and Formations Sanitaires Privées de Base. NB: negative binomial model.

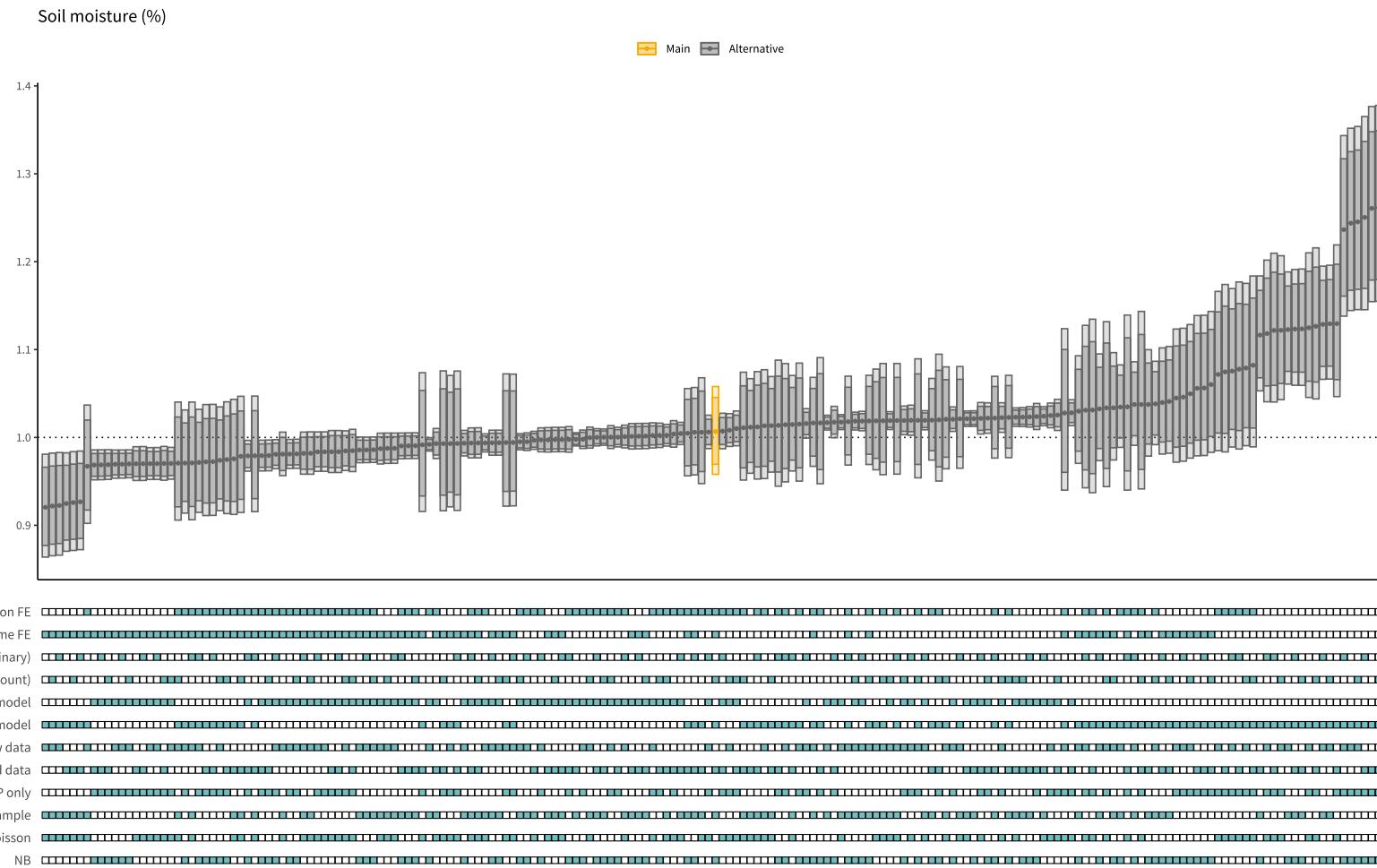


Figure 13: Specification curve depicting the effect estimates and confidence intervals for mean monthly soil moisture (percent saturation) across 192 models. In the top panel, estimated incidence rate ratios (IRRs) across different models are depicted as circles; the darkly and lightly shaded regions above and below these circles correspond to 95% and 99% confidence intervals of these estimates, respectively. The dotted horizontal line depicts a null effect. The IRR estimate and confidence intervals of the preferred model, Model 4, are highlighted in orange. Below each model, a legend of shaded and unshaded boxes indicates which modeling decisions correspond to a given model, with boxes shaded teal showing active features. FE: fixed effects. CSB/FSP: Centres Santé de Base and Formations Sanitaires Privées de Base. NB: negative binomial model.

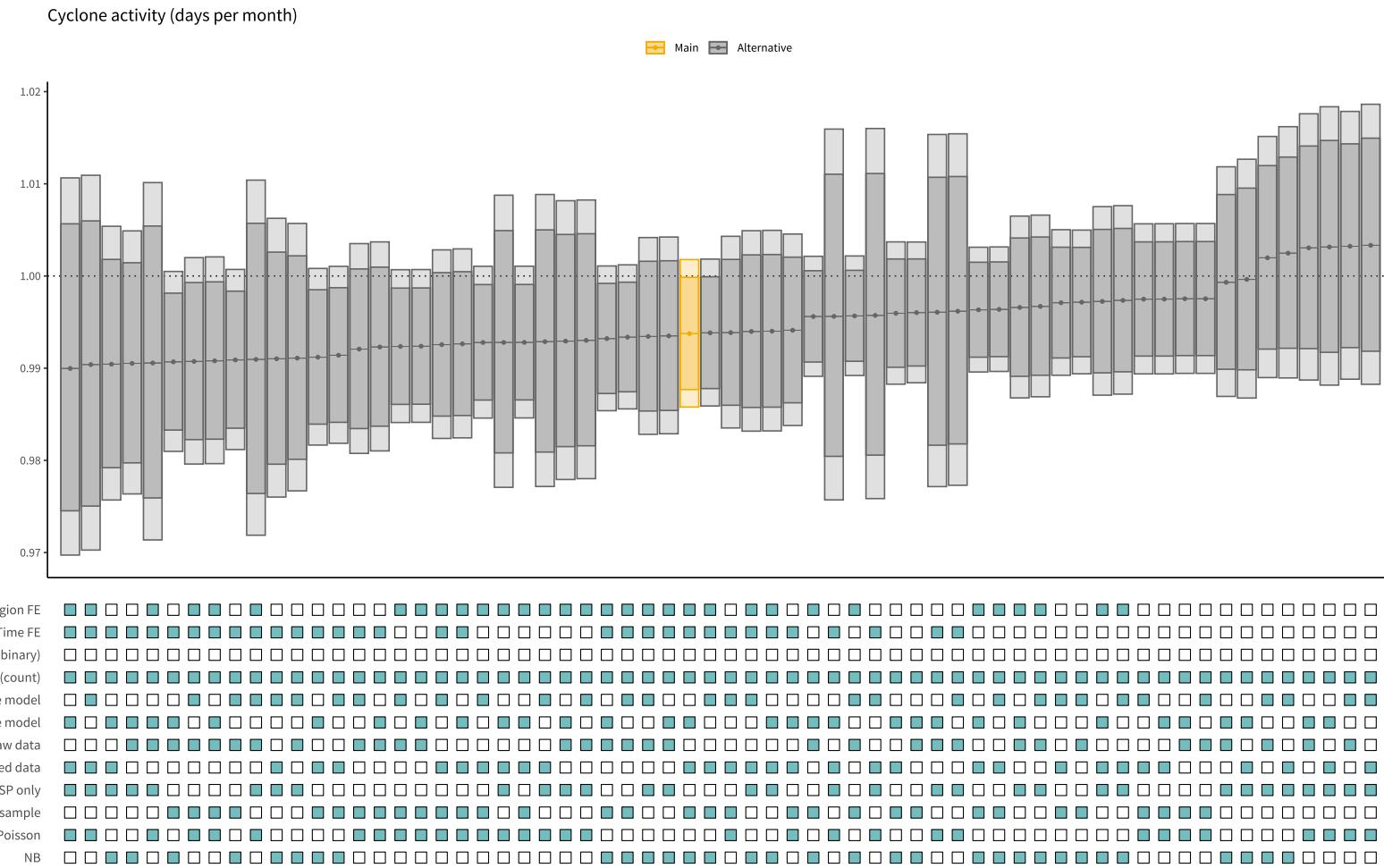


Figure 14: Specification curve depicting the effect estimates and confidence intervals for cyclone activity (measured as days with a tropical storm or cyclone impacting Madagascar in a month) across 64 models. In the top panel, estimated incidence rate ratios (IRRs) across different models are depicted as circles; the darkly and lightly shaded regions above and below these circles correspond to 95% and 99% confidence intervals of these estimates, respectively. The dotted horizontal line depicts a null effect. The IRR estimate and confidence intervals of the preferred model, Model 4, are highlighted in orange. Below each model, a legend of shaded and unshaded boxes indicates which modeling decisions correspond to a given model, with boxes shaded teal showing active features. FE: fixed effects. CSB/FSP: Centres Santé de Base and Formations Sanitaires Privées de Base. NB: negative binomial model.

2.4 Discussion

In our study of health facilities in Madagascar, we investigated how temperature, soil moisture, and exposure to cyclone activity impacted monthly counts of patient visits for mental and neurological disorders reported by 3,413 facilities between 2010 and 2020. This study had three major findings. First, we found evidence of a statistically significant reduction in reported mental health visits of approximately 4.5% associated with mean monthly temperature, with warmer temperature being, on average, associated with 2 to 3 fewer visits per month. According to our multiverse analysis, the statistically significant inverse association we observed was robust to numerous specifications, while our subgroup analysis indicated that this association was primarily localized in the highland subhumid forest ecoregion. Second, we found evidence to suggest potential lagged impacts, with higher soil saturation being associated with an 8.5% elevation in reported visit counts in the subsequent quarter. We also found evidence of possible effect heterogeneity, with each percentage point increase in soil moisture leading to an *elevation* of visits in the dry deciduous forest ecoregion and a *decrease* in visits in the highland subhumid forests. Third, while our lagged models and multiverse analysis suggested the possibility of a negative relationship between cyclone activity and mental health visits reported in Madagascar, the marginal effects associated with cyclone duration were negligible, and we did not observe sufficient statistically significant evidence to reject the null assumption of no association at a level of 0.01.

It is important to note in our interpretation of these findings that the true relationship between reported mental health visits and actual cases of mental disorders is not well understood, particularly in Madagascar, where there is no epidemiological data on the prevalence or distribution of mental disorders in the general population. The changes in mental health visits could reflect changes in the actual cases of mental disorders but could also result from the influence of CCEs on help-seeking behavior, diagnostic capacity, or other factors. Additionally, it has been widely recognized that

the majority individuals with mental disorders often do not receive any mental health treatment, particularly in low-income settings.⁹

With these caveats in mind, our results concerning an inverse relationship between temperature and visits related to mental and neurological disorders are nonetheless surprising and run counter to our expectation, given that a robust body of literature has documented that heat and heat waves have a harmful effect on mental health outcomes⁸³ and general aspects such as mood,⁸⁴ life satisfaction,⁸⁵ and happiness.⁸⁶

Research in subtropical regions, however, has found that the association between temperature and mental disorders is likely non-linear, with both extreme cold and extreme heat being associated with harmful effects on mental morbidity.⁸⁷ Degree increases in temperature, therefore, could show a protective effect in colder months, resulting in an overall inverse association between temperature and reported cases in a sample with few extremely warm months. This is consistent with our marginal effect estimates, which show the greatest reduction in visit counts being associated with degree increases at the coldest temperatures. In addition, this explanation would be consistent with our subgroup analysis, which found that the protective effect of warmer temperatures was observed only among facilities in the central high plateau—where temperatures are generally cooler than those in the surrounding lowlands.

An alternative explanation could be that access to mental health services is limited in warmer months due to factors such as increased demand for medical services related to heat-related illnesses. A crowding out of provider availability due to physical complaints in warmer months (for example, malaria-related fever) could lead to decreased availability of provider access for mental disorders, especially at primary health facilities with already limited diagnostic capacity. Understanding how climate conditions in Madagascar impact the broader burden of disease, including physical conditions, is the subject of current investigation, and will lend further insight into potential

mechanistic explanations for our findings.

With respect to soil moisture, to the best of our knowledge, there have been no studies that directly explore the association between soil saturation and mental health in non-emergency conditions. In terms of extremely low soil moisture, evidence from droughts suggest potential indirect pathways to worsened mental health outcomes,⁸⁸ but these impacts are not well characterized and may not manifest over a short time horizon.⁸⁹

Though incidence rate ratios and marginal effect estimates associated with soil moisture were not statistically significant in our main analysis, we observed a significant association of higher soil moisture and visits for mental health complaints in the following quarter, echoing similar findings from U.S. meteorological data linking higher precipitation with worsened mental health.⁹⁰ In addition, our subgroup analysis also indicated significant and diverging effects among different ecoregions. In particular, we found that greater soil moisture was associated with more visits reported in the eastern lowlands and the northern dry deciduous forests, which echoes the geographic concentration of flood risk in Madagascar.⁹¹ Conversely, the observed (though statistically modest) reduction in visits associated with higher soil moisture in the desert and xeric shrublands overlaps with the concentration of drought risk, where increased soil moisture could be taken as an indicator of reduced drought vulnerability. It is important to note, however, that the time frame of available GESIS data excludes the most severe period of the ongoing drought in Madagascar, limiting our ability to directly study the impact of the current crisis on population mental health in this analysis. Further research could leverage spatial reanalysis data on precipitation to further characterize these associations.

Madagascar's wet season is marked by frequent tropical storms and cyclones—the intensification of which has been linked to rising temperatures in the Indian Ocean.⁹² In the majority of our models in the multiverse analysis, we found that months with greater duration of cyclone activity were

associated with *fewer* monthly report visits for mental disorders, though none of these models were significant at the threshold of 0.01. In numerous studies, cyclones and similar disasters have been found to worsen mental health;⁹⁰ however, these storms may also result in numerous conditions that make access to mental health resources more challenging. Disruptions to regular health care services and an intensification of acute health needs⁹³ in the post-disaster period could result in barriers to receiving care for incident mental disorders,⁹⁴ which would be consistent with a reduction in reported visits despite a rise in mental distress.

Failure to observe effect heterogeneity in our subgroup analysis of the association of cyclone activity with reported monthly visits likely is due, in part, to our specification choice to define exposure to cyclone activity without geographic variation in intensity. While we felt justified in opting for a simplified indicator, given that storms in Madagascar typically impact the whole of the island, a more nuanced (but data-hungry) approach could define exposure with greater geographic precision based on additional climate metrics, including peak wind, rainfall, and distance from the storm's track.⁹⁵

A further weakness of our analysis is that inherent to any ecological study relying on aggregated data: the lack of individual-level data substantively constraints our ability to draw causal inferences, account for and exclude potential confounding variables, and ascertain mechanistic explanations for observed associations. While these are important caveats in interpreting our results, we assert that there is considerable value in leveraging existing data from national health management information systems to generate epidemiologic evidence. The opportunity to employ health information system data is particularly important in countries like Madagascar, where, as in many LMICs, HMIS information is routinely generated but systematically underutilized.⁹⁶

Despite these limitations, our study has important implications for future research on the relationship between climate change exposures and population mental health. By leveraging reported

visits from over three thousand health facilities over ten years, utilizing the most comprehensive sources of climate data available, and linking the two via a rigorous, multistep geolocating process, our analysis demonstrates how routine health system data may offer valuable insights, particularly when other epidemiological data are not available. As one of the only studies to investigate mental health and climate in Africa using national HMIS data, our findings also underscore the need for further research to understand the relationships and pathways between changing climate and population mental health, particularly countries most vulnerable to climate change. Finally, our findings and interpretations highlight the importance of local knowledge and collaboration with local ministries in global health research, to make best use of existing data and to foster research to support health system strengthening. We believe that this approach to research is essential for understanding the complex relationships and mechanisms linking climate change exposures to mental health, as well as identifying strategies to mitigate these impacts amid the unfolding global climate crisis.

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2.5.1 Author contributions

All authors contributed to study conception, methodology, and interpretation. DA oversaw data acquisition, programming, formal analysis, visualization, and the first draft of the manuscript.

2.5.2 Funding statement

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2.5.3 Declaration of interests

We declare no competing interests.

2.5.4 Data sharing statement

All codes used for the analysis in this article are available on GitHub (https://github.com/darias5/madagascar_mh).

3 The impact of COVID-19 vaccine developments on Google COVID-19 search trends for mental health symptoms: a controlled interrupted time series analysis

Daniel Arias

Background: A key obstacle to studying the impact of policies on population mental health in the U.S. is a lack of appropriate high frequency surveillance data. A potential marker of population mental health is the use of Internet search data, which enables real-time, large-scale analysis of evolving mental health issues.

Methods: I utilized controlled interrupted time series approaches to evaluate whether the development of COVID-19 vaccines reduced Google searches related to symptoms of depression and anxiety in U.S. states and counties. I examined how search trends changed following the announcement of vaccine safety and efficacy data for mental health symptoms compared with physical health symptoms, and estimated associations between vaccine announcement and changes in mental health symptom search density. I adjusted for state, month, and weekday effects, and applied numerous sensitivity analyses to assess the robustness of the findings. To explore heterogeneity by predominate political affiliation, I also tested whether the estimates varied among states and counties that predominantly voted for the Democratic Party candidate in the 2020 presidential election compared to the Republican candidate.

Findings and interpretation: Under the main model specification, I observed reduced search density for depression and anxiety associated with the announcement of vaccine safety data. For searches related to depression, I observed a sustained decline in search density of -0.029 percentage points per day (99% confidence interval (CI): -0.031 to -0.027; $p < 0.0001$) and an immediate downward level shift of -0.143 percentage points (99% CI: -0.185 to -0.100; $p < 0.0001$) relative to

comparable symptom searches. For anxiety, I estimated a similar slope change of -0.035 percentage points per day (99% CI: -0.037 to -0.032; $p < 0.0001$) and a level shift of -0.273 percentage points (99% CI: -0.333 to -0.212; $p < 0.0001$). I did not observe significant variations across predominately Democrat or Republican voting states and counties, and the findings were robust to alternative specifications of bandwidth, fixed effects, and data cleaning decisions. If symptom search density echoes population health, the results would indicate that announcements regarding the development of safe and effective COVID-19 vaccines led to a robust and sustained improvement in mental health. These findings underscore the importance of timely and transparent communication and highlight the potential application of high frequency internet search data for population mental health surveillance.

Keywords: *mental health; controlled interrupted time series; COVID-19 vaccines; United States; Google searches.*

3.1 Introduction

The COVID-19 pandemic has had a profound effect on the mental health and well-being of individuals worldwide. Studies from Australia,⁹⁷ China,^{98–107} Denmark,¹⁰⁸ Europe,¹⁰⁹ Iran,¹¹⁰ Ireland,¹¹¹ Italy,^{112,113} Nepal,¹¹⁴ New Zealand,^{115,116} Spain,^{117,118} Turkey¹¹⁹, the United Kingdom¹²⁰, and the United States^{121,122} have reported high levels of anxiety (6-51%), depression (15-48%), and post-traumatic stress disorder (7-54%) associated with the onset of the pandemic. In the United States, approximately four in ten adults reported experiencing symptoms of anxiety or depression in December 2020—a four-fold increase from January-June 2019.¹²³ Globally, it has been estimated that the prevalence of depression and anxiety during the COVID-19 pandemic may be as high as 24% and 21%, respectively.^{124,125} This striking burden has been described as a mental health crisis¹²⁶ and as a pandemic in its own right.¹²⁷

While COVID-19 continues to bring unprecedented challenges to societies around the world, the development and distribution of safe and effective vaccines has fundamentally changed the trajectory of the pandemic. Beyond the physical benefits vaccines provide in reducing the risk of infection and associated morbidity and mortality, a growing body of evidence suggests that vaccination has also contributed to improved mental health.^{128–131} While there is limited international data on the secondary mental health impact of COVID-19 vaccination, research drawing from the U.S. Census Bureau’s Household Pulse Survey has found that benefits of vaccination may include up to a 30% reduction in symptoms of anxiety and depression among vaccinated adults,¹²⁸ while research using the University of Southern California Understanding America Survey suggests a reduction in loneliness associated with greater social interactions following vaccination.¹³²

While this literature suggests that receiving a COVID-19 vaccine can improve mental health, the potential mental health benefits of announcements regarding the development of vaccines have received comparatively less attention.^{133,134} In the context of a deadly pandemic, the announcement

of a safe and effective vaccine could be a powerful signal, providing a psychological boost that the worst might soon be mitigated. Studying how population mental health may have been impacted by the release of vaccine efficacy and safety trial data may provide insights into how emotional well-being changed throughout the pandemic in response to these signals, which, in turn, could inform public health communication and contribute to the understanding of how the public responds to information about vaccines—a necessary understanding for increasing vaccine uptake and trust in public health responses.

A key obstacle to studying the impact of public health policies on population mental health, however, is a lack of appropriate high frequency surveillance data. A potential marker of population mental health is the use of internet search data, which enables real-time, large-scale analysis of evolving mental health issues. A recently published evaluation of Google's COVID-19 Search Trends Symptoms Dataset¹³⁵ found a strong correlation between search trends for depression and anxiety with indicators of mental health services utilization (reported in the U.S. Census Household Pulse Survey) and rates of emergency department visits for mental health conditions (from the U.S. Centers for Disease Control and Prevention's (CDC) National Syndromic Surveillance Program).¹³⁶ If taken as a reasonable proxy for mental health disorders, search data can provide valuable information on how population mental health reacts to real-time events, enabling policymakers to better respond to mental health needs in a timely manner.

This study analyzes whether news announcements (in November 2020) regarding the imminent availability of safe and effective COVID-19 vaccines impacted population mental health—even before these vaccines were made available to the public. Using Google search density data, I applied interrupted time series approaches to investigate how these announcements might have affected search trends for mental health symptoms in the U.S. and five other countries where data were available: Australia, Ireland, New Zealand, Singapore, and the United Kingdom. Owing to emerging

evidence that political ideology may be a predictor of confidence in public health and vaccine hesitancy,^{137–139} I further explored whether changes in search trends for mental health symptoms varied across U.S. states and counties that predominantly voted Democrat versus Republican in the 2020 presidential election. These findings suggest declines in density for searches related to anxiety and depression in all of the countries examined; in the U.S., these declines were found to be consistent irrespective of political ideology.

3.2 Methods

3.2.1 Data sources

3.2.1.1 Vaccine announcements I took November 16, 2020 as the date of the first credible signal of the imminent availability of safe and effective COVID-19 vaccines. On November 9th, Pfizer announced that early vaccine trial data showed 90% efficacy¹⁴⁰ and on the 16th, Moderna announced preliminary results showing 95% efficacy.¹⁴¹ While U.S. Food and Drug Administration (FDA) Emergency Use Authorization (EUA) was not granted until December, the concurrent announcements of vaccine efficacy were widely reported and interpreted by many public health practitioners, policymakers, and the general public as a substantial signal of a new phase of the pandemic, with Moderna’s chief executive officer calling the news “a game changer” in the fight against COVID-19.

3.2.1.2 Symptoms dataset I accessed aggregated national and subnational data from Google’s COVID-19 Search Trends Symptoms Dataset¹³⁵ (hereafter referred to as the symptoms dataset) between January 1, 2020 and April 1, 2021. The symptoms dataset provides time series data of search term density, standardized to pairs of health symptoms and regions (e.g., searches for depression in Australia or fever in Cook County, Illinois) and normalized within each pair based on the symptom’s

relative popularity. The time series of search density for each symptom-region pair also contains artificial noise, as Google's differential privacy technique to data aggregation and anonymization adds random noise to protect user privacy (the errors are symmetrically distributed).¹³⁵

Search density data for over 400 symptoms were reported by Google across national and subnational regions of six predominately English-speaking countries: Australia, Ireland, New Zealand, Singapore, the United Kingdom, and the United States. In the U.S., subnational regions include states and counties. Because the aggregated search density data were constructed based on relative search population within each region, I could not compare search density for specific symptoms across different regions; however, comparing search density within regions (or a group of regions) was feasible both over time and across different symptoms.

I utilized three levels of region: 1) national level for the six countries; 2) U.S. state level data across 50 states and the District of Columbia; and 3) U.S. county level data across 2,505 counties (though there are over 3,000 counties in the U.S., due to data privacy concerns, smaller county results were not included in the symptoms dataset). Following the convention of the symptoms dataset, I will refer to the geographic units (e.g., states, counties, and nations) within the data as “regions.”

3.2.1.3 Voting dataset I obtained county-level presidential election results for 2020 from the MIT Election Data and Science Lab,¹⁴² which I used to calculate aggregate county and state votes (including absentee, early, and election day ballots) for each candidate. The aggregate votes were then used to determine vote share and margins (e.g., the percentage points difference in vote share between the winning candidate and the runner up). Applying a similar approach as other research into COVID-19 and political party inclination,¹⁴³ I used these margins to sort counties and states into quintiles, such that the 20% most Republican-voting localities appearing in the symptoms

dataset were sorted into the first quintile and the 20% most Democratic-voting localities sorted into the fifth quintile.

3.2.1.4 Population data Population estimates for 2020 by Federal Information Processing Standards (FIPS) code were obtained from the U.S. Department of Agriculture (USDA) Economic Research Service.

3.2.2 Statistical analysis

All analyses were conducted using R software (version 4.2.1).⁴⁹

3.2.2.1 Modeling approach I used an interrupted time series (ITS) approach to model the Google search density for a given symptom d using the following baseline equation:

$$Y_{d,g,i} = \lambda_0 + \lambda_1 time_t + \alpha_d Post_{d,i} + \beta_d time_t * post_{d,i} + \theta_r + T'_t \chi + \epsilon_{it} , \quad (3.1)$$

where $time_t$ is a continuous variable that captures the days before the vaccine announcement ($time_0$), $Post_i$ is an indicator variable equal to 1 in the period after the announcement (0 otherwise), θ_r indicates a series of fixed effects for each region (r), $T'_t \chi$ is a matrix of time fixed effects (i.e., month and day of week), and ϵ_{it} is an error term. α_d can be interpreted as a level change associated with the announcement date—that is, the immediate difference in search density for a disease d following November 19, 2020; β_d —the slope change—can be interpreted as the sustained change in search density in the days following November 16th.

I applied this model for all available 420 diseases with county-level data. As search density may rapidly change in response to new announcements, I trimmed the bandwidth of dates to fit the model to 40 days before and after November 16, 2020.

To control for time-varying confounders which may affect symptom search trends, I applied

a controlled interrupted time series (CITS) approach to contrast how searches for mental health symptoms varied above and beyond changes in search density for a comparable physical complaint (i.e., headaches).

After reviewing the list of symptoms for which search density data were available, I identified the following 18 mental health symptoms: anxiety, Asperger syndrome, attention deficit hyperactivity disorder, binge eating, clouding of consciousness, compulsive behavior, depersonalization, depression, dysphoria, generalized anxiety disorder, impulsivity, major depressive disorder, manic disorder, mood disorder, panic attack, psychosis, self harm, and suicidal ideation.

For each of these symptoms, d , I ran the following model:

$$Y_{d,it} = \lambda_0 + \lambda_1 time_t + \lambda_2 Post_t + \lambda_3 time_t * Post_t + \alpha_d mhealth_{di} + \beta_d time_t * mhealth_{di} + \delta_d Post_i * mhealth_{di} + \gamma_d time_t * Post_i * mhealth_{di} + \theta_g + T_t' \chi + \epsilon_{it} , \quad (3.2)$$

where $mhealth_{di}$ equals 1 if the observation is for a mental health symptom d (0 for headaches).

The estimates of interest are given by δ , which reflects the additional level shift among symptom searches (compared to searches for headaches) after vaccine announcement, and γ , the additional relative change in search density over time (i.e., slope change).

Given the high number of observations in the sample, I evaluated significance against an alpha of 0.01, and I constructed 99% confidence intervals (CIs) using heteroskedasticity-robust standard errors.

3.2.2.1.1 Sensitivity analysis As with other quasi-experimental methods, it is recommended that the modeling specifications be evaluated using a sensitivity analysis. To do so, I defined a list of seven methodological choices concerning data processing and modeling assumptions and interacted these choices to generate all plausible combinations. These combinations were then conducted to allow for a multiverse analysis to identify how sensitive effect estimates and CIs were to different methodological choices. The criteria used to generate the plausible model combinations are outlined

in Table 3.1.

Table 3.1: Alternative specifications, data processing, and modeling decisions for multiverse analysis. *: preferred specification.

1. Data cleaning for outcome data
a) Linear interpolation to replace outliers *
b) No adjustment (raw data)
2. Region level
a) U.S. counties *
b) U.S. states
c) International (n = 6)
3. Bandwidth
a) ± 40 days *
b) ± 50 days
c) ± 60 days
4. Day of week fixed effects
a) Included *
b) Excluded
5. Month fixed effects
a) Included *
b) Excluded
6. Regional fixed effects
a) Included *
b) Excluded

First, I considered the role of data cleaning in the outcome data, which involved outlier smoothing using Friedman’s nonparametric super smoother regression estimator.⁷⁷ Second, I compared the level of region of aggregated data, using U.S. counties, U.S. states, and, finally, national trends from the six counties in the sample. Third, I evaluated sensitivity to the specification of the bandwidth cut-off around the announcement date, extending it from ± 40 days to ± 50 and ± 60 days. Fourth, I toggled whether to account for day of week fixed effects; fifth, I toggled month fixed effects; and sixth, I toggled regional fixed effects (i.e., fixed effects for states in the U.S. state level data, fixed effects for counties in the U.S. county level data, etc.).

Interacting these choices resulted in 144 plausible models for each symptom. Each model was

run for all 18 mental health related symptoms, resulting in 2,736 models being conducted overall.

3.2.2.1.2 Subgroup analysis Two subgroup analyses were conducted to investigate the generalizability of the findings of the main analysis and to explore potential heterogeneities in measures of association.

The first subgroup analysis applied the CITS approach against all 18 mental health related symptoms against search data from each of the six countries in the sample, using the nationally aggregated data. This analysis aimed to investigate the extent to which effects observed in U.S. states and counties were also seen in other countries.

The second subgroup analysis applied the CITS approach to the 20% most Republican-voting localities (hereafter referred to as red states/counties) and to the 20% most Democratic-voting localities (hereafter referred to as blue states/counties) based on 2020 presidential election vote share. The subgroup analysis comparing CITS effect estimates in blue versus red states aimed to investigate whether the initial response to imminent safe and effective COVID-19 vaccines showed evidence of heterogeneity by predominant political ideology, under the hypothesis that if conservative voters were more likely to be averse to vaccination, any impact on mental health related symptom search density from the announcement of upcoming vaccines would be lesser in red states and counties compared to blue ones.

3.2.3 Ethics statement

The Institutional Review Board (IRB) of the Harvard T.H. Chan School of Public Health determined that this study was not human subjects research and that additional review was not required (protocol number: IRB23-0095, determined on January 25, 2023).

3.3 Results

The estimates for the immediate (level shift) and sustained (slope change) effects associated with the announcement of vaccine safety and efficacy data on search density for all 420 are presented in Figure 15.

For most symptoms, search density exhibited negligible differences following the announcement, with small positive level shifts offset by modest negative slope changes. For four mental health symptoms, however, I observed relatively large, negative slope changes for searches for anxiety (-0.078, $p < 0.0001$, 99% CI: -0.082 – -0.073), depression (-0.059, $p < 0.0001$, 99% CI: -0.062 – -0.056), major depressive disorder (MDD)(-0.053, $p < 0.0001$, 99% CI: -0.056 – -0.050), and attention deficit hyperactivity disorder (ADHD)(-0.046, $p < 0.0001$, 99% CI: -0.048 – -0.043). With respect to level shifts, changes for anxiety (0.035, $p = 0.080$, 99% CI: -0.016 – 0.086) and depression (0.107, $p < 0.0001$, 99% CI: 0.071 – 0.143) were close to zero, while those for MDD (0.230, $p < 0.0001$, 99% CI: 0.197 – 0.264) and ADHD (0.235, $p < 0.0001$, 99% CI: 0.202 – 0.268) were approximately 0.3 percentage points.

While the ITS analysis provided suggestive evidence that search density for mental health symptoms might have changed in the post-announcement period, it also highlighted that searches may have generally changed across other diseases at the same time. The CITS estimates of each mental health symptom (Figure 16) using searches for headaches as a comparison broadly echoed the ITS analysis, with most conditions showing level and slope changes close to 0. For three conditions, the CITS analysis showed relatively large slope changes with searches for anxiety (-0.035, $p < 0.0001$, 99% CI: -0.037 – -0.032), depression (-0.029, $p < 0.0001$, 99% CI: -0.031 – -0.027), and MDD (-0.012, $p < 0.0001$, 99% CI: -0.013 – -0.010), all showing sustained declines. All three symptoms had relatively large slope changes in the ITS analysis. In addition, the CITS level shift (i.e., the relative immediate effect) for anxiety was -0.273 percentage points ($p < 0.0001$, 99% CI: -0.333 –

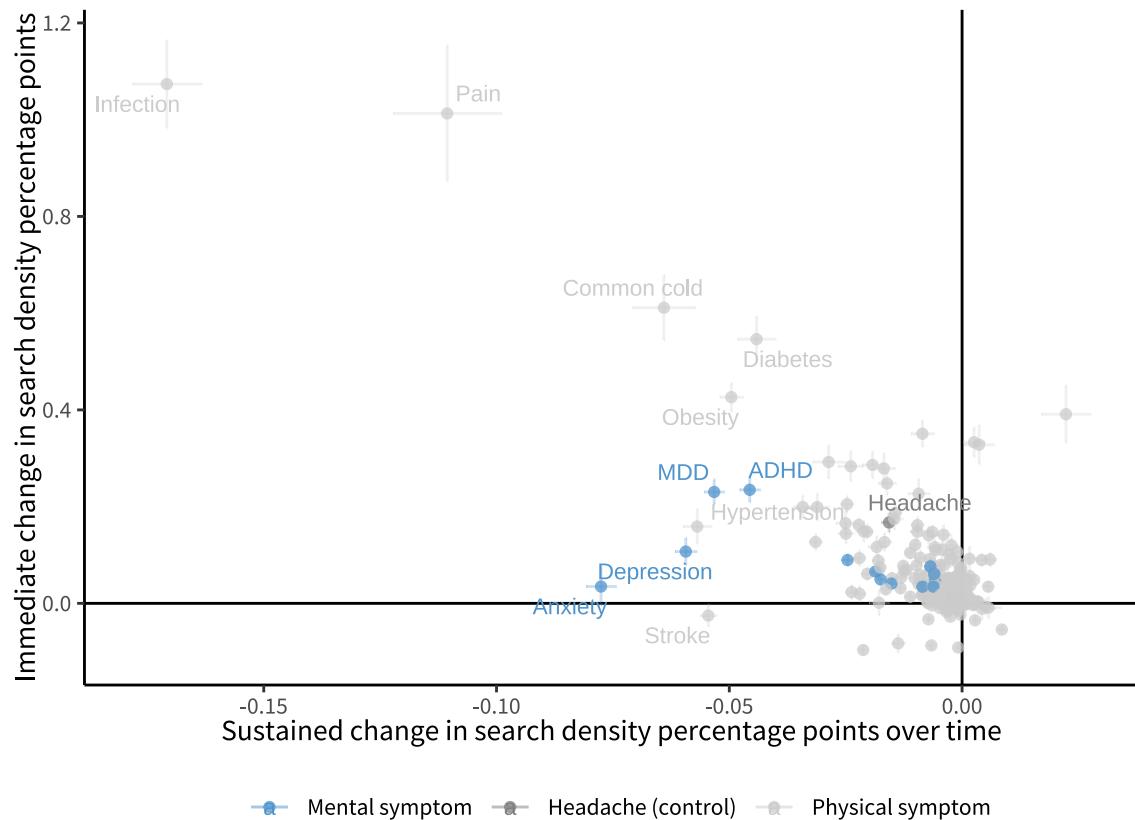


Figure 15: Interrupted time series effect estimates and confidence intervals by symptom. Effect estimates are presented by points; for each symptom, the estimated slope change per day is shown on the x-axis, while the level shift over the post-announcement period is shown on the y-axis. The horizontal and vertical bars next to each point represent the 99% confidence intervals for the estimate slope change and level shift, respectively. Mental health-related symptoms are shown in blue, while physical symptoms are shown in grey. ADHD: Attention deficit hyperactivity disorder. MDD: Major depressive disorder.

-0.212), a decrease double in magnitude compared to most estimates for other symptoms.

In both the analyses, search trends for anxiety, depression, and MDD showed potential immediate and sustained declines in density following November 16th. Search density for these three symptoms and the comparison search data for headaches is plotted in Figures 17 through 19 at the level of U.S. states, U.S. counties, and international data. I observed relatively strong concordance between the CITS estimates and the observed trends in the data, with strong fit to both mental health symptoms and headaches. I further observed strong within-week patterns in searches, supporting the inclusion of fixed effects to account for this weekly periodicity.

The multiverse analysis further underscored the robustness of the findings concerning the relatively large negative immediate and sustained effects on searches for anxiety and depression, in particular (Figure 20). For anxiety, all 144 models had negative level shifts and slope changes. For depression, all 144 models had negative slope changes, of which only 24 models had any positive level shift. For MDD, I similarly observed a universally negative slope change in all 144 models; however, the majority of models showed a positive level shift (96 models), whereas only 48 showed a downward level shift.

Slope changes and level shifts for anxiety, depression, and MDD are reported for each combination (144 models) in Figure 21. Examining the plausible model combinations of the multiverse analysis for these three symptoms underscored the importance of regional level to inference, as the use of county-level data (with a greater number of observations) consistently showed similar effect estimates compared to state level estimates, but with much tighter CIs, even when geographic fixed effects and narrower bandwidths were included. Across all models, the sustained change in search density for anxiety and depression was negative and significant with an alpha of 0.01. In terms of the estimated level shifts, 90 models for anxiety (62%) had a statistically significant negative change, compared to 0 models with a positive one. For depression, of the 64 models with a statistically

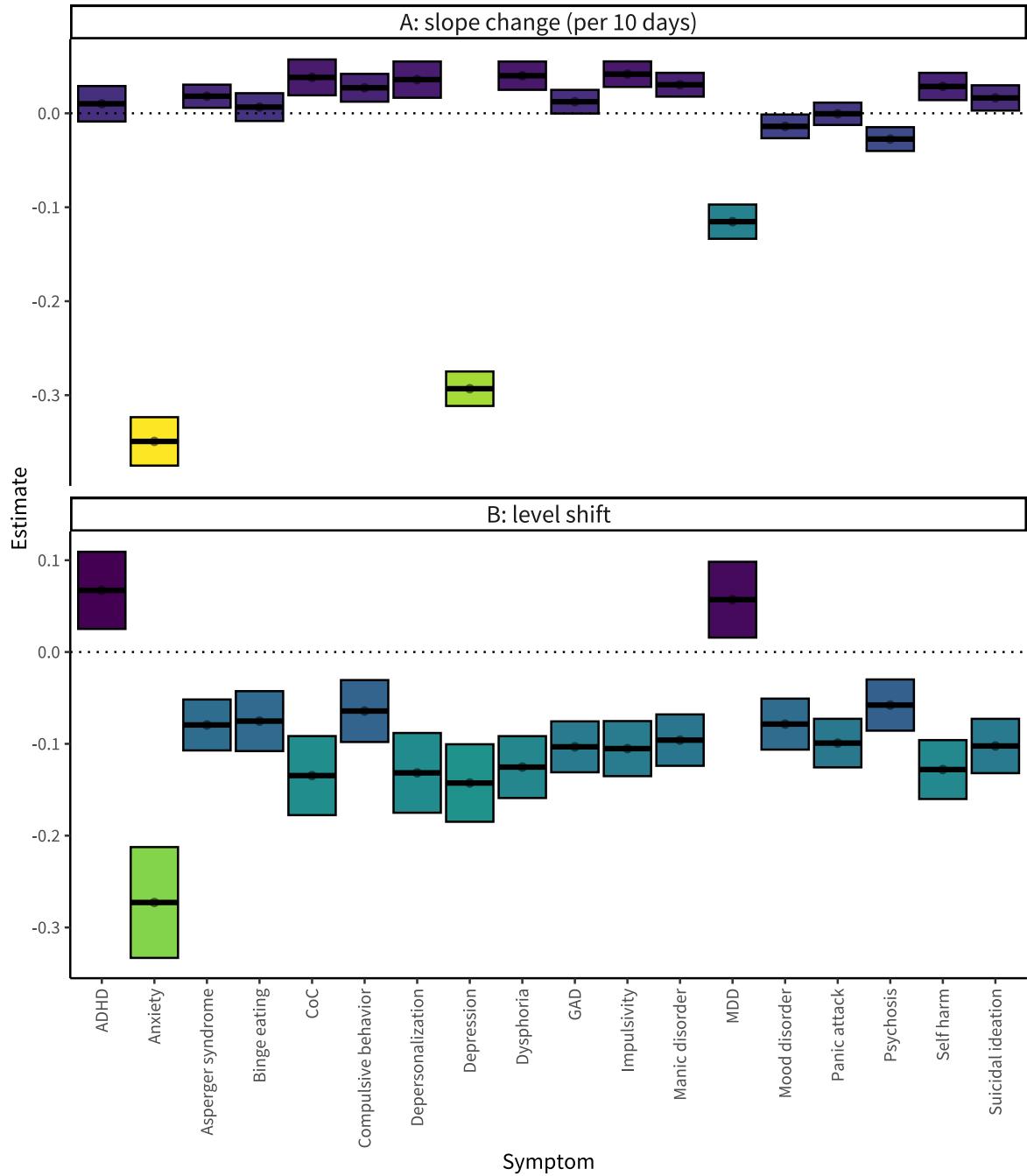


Figure 16: Controlled interrupted time series effect estimates (A: slope change per 10 days and B: level shift) for Google Search density by symptom. Effect estimates are represented as thick, horizontal lines in between colored bands, which represent the 99% confidence intervals for the estimates. Colors reflect the sign and magnitude of effect estimates. Dark blue values above zero indicate an increase in search density, while the yellow and green negative values indicate a decrease. The dotted horizontal line depicts a null effect. ADHD: Attention deficit hyperactivity disorder. CoC: clouding of consciousness. GAD: Generalized anxiety disorder. MDD: Major depressive disorder.

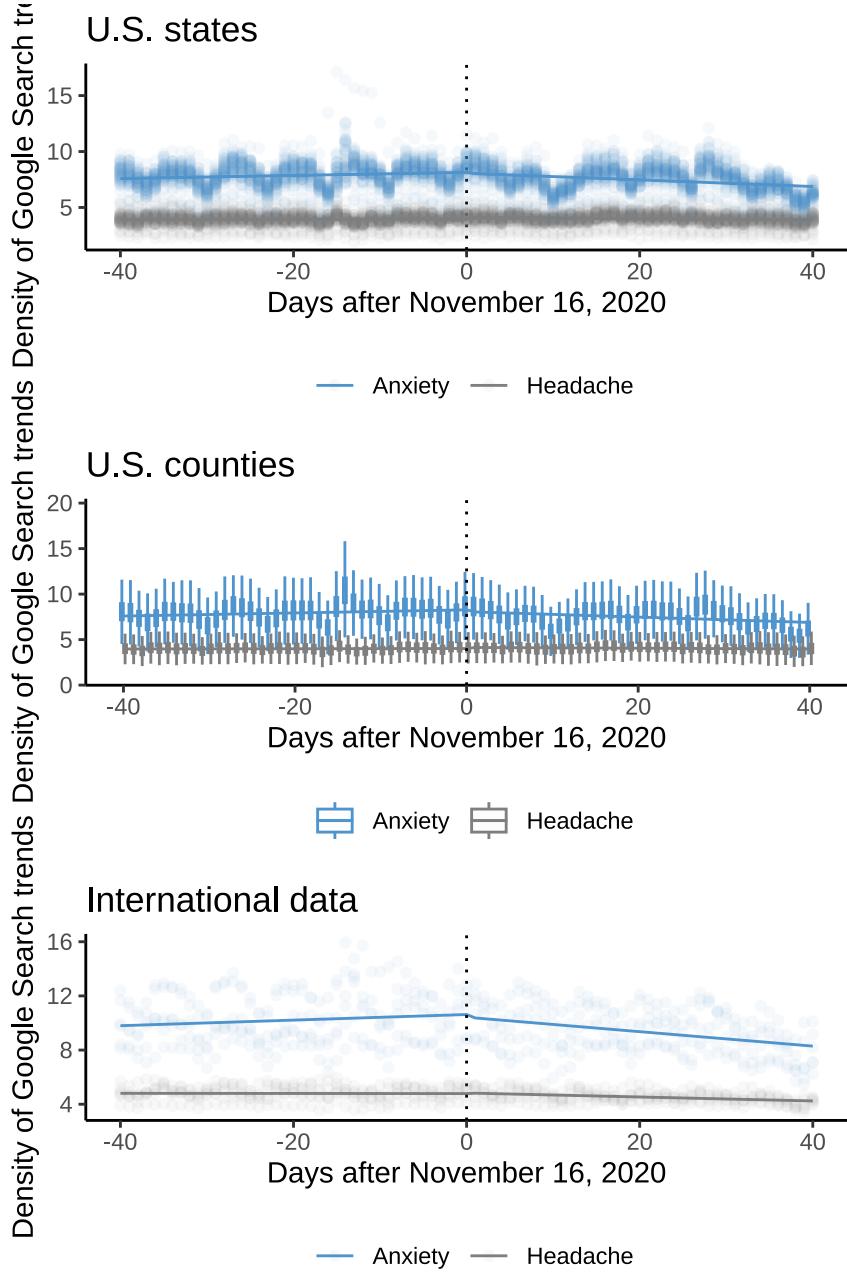


Figure 17: Density of Google Search trends for anxiety, by region and as a function of time. In each row, search density data for two symptoms are displayed: anxiety in blue and headaches in grey. In the first row, data from U.S. states are shown, where each point represents the search density of a specific symptom on a specific date in a specific state. In the second row, data from U.S. counties are shown; because of the large number of counties reporting data, county-level search data are summarized as daily boxplots. In the third row, national data from Australia, Ireland, New Zealand, Singapore, the United Kingdom, and the United States are shown. Each graph shows the density of symptom searches on the y-axis, while time is centered and displayed as days prior to and following November 16, 2020 on the x-axis. The solid lines show predicted lines of best fit under a basic controlled interrupted time series model (i.e., no fixed effects). U.S.: United States.

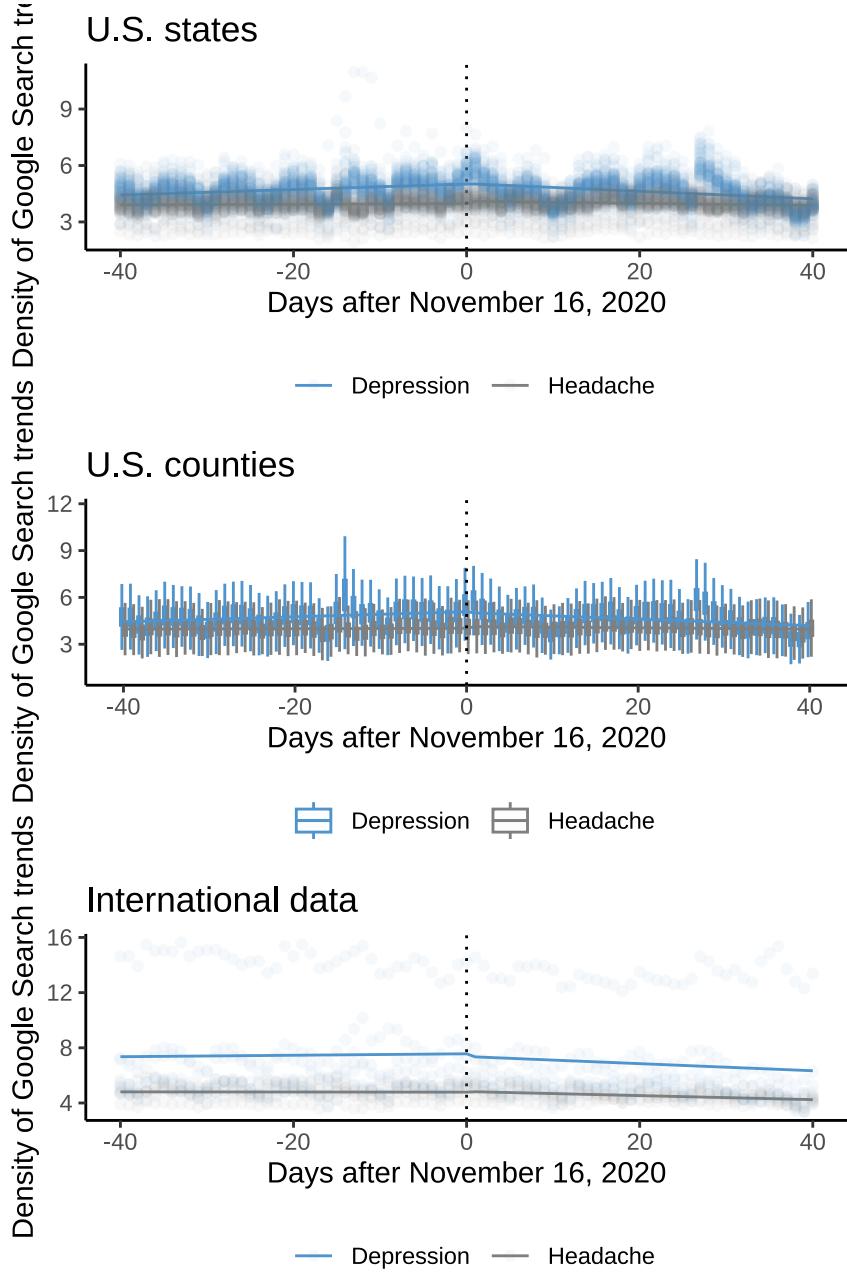


Figure 18: Density of Google Search trends for depression, by region and as a function of time. In each row, search density data for two symptoms are displayed: depression in blue and headaches in grey. In the first row, data from U.S. states are shown, where each point represents the search density of a specific symptom on a specific date in a specific state. In the second row, data from U.S. counties are shown; because of the large number of counties reporting data, county-level search data are summarized as daily boxplots. In the third row, national data from Australia, Ireland, New Zealand, Singapore, the United Kingdom, and the United States are shown. Each graph shows the density of symptom searches on the y-axis, while time is centered and displayed as days prior to and following November 16, 2020 on the x-axis. The solid lines show predicted lines of best fit under a basic controlled interrupted time series model (i.e., no fixed effects). U.S.: United States.

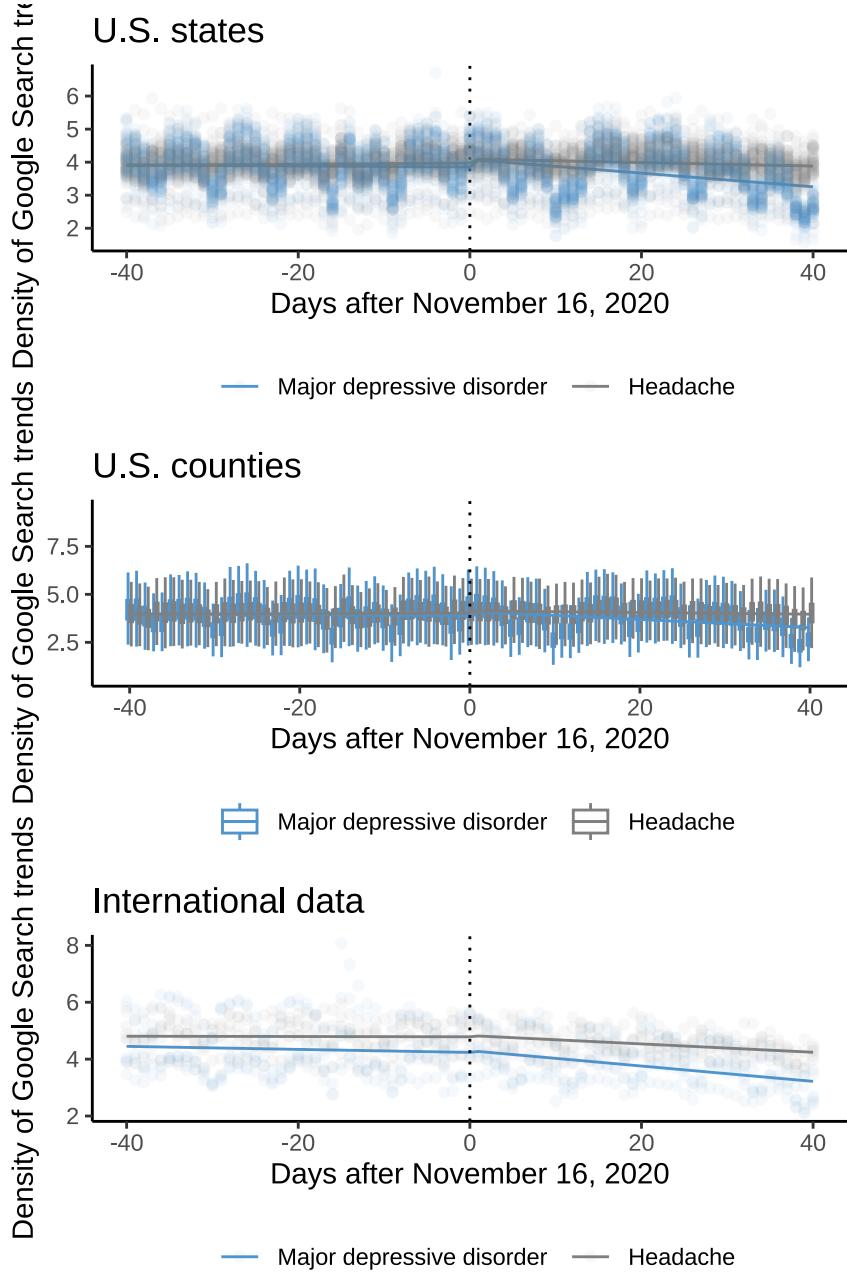


Figure 19: Density of Google Search trends for major depressive disorder (MDD), by region and as a function of time. In each row, search density data for two symptoms are displayed: MDD in blue and headaches in grey. In the first row, data from U.S. states are shown, where each point represents the search density of a specific symptom on a specific date in a specific state. In the second row, data from U.S. counties are shown; because of the large number of counties reporting data, county-level search data are summarized as daily boxplots. In the third row, national data from Australia, Ireland, New Zealand, Singapore, the United Kingdom, and the United States are shown. Each graph shows the density of symptom searches on the y-axis, while time is centered and displayed as days prior to and following November 16, 2020 on the x-axis. The solid lines show predicted lines of best fit under a basic controlled interrupted time series model (i.e., no fixed effects). U.S.: United States.

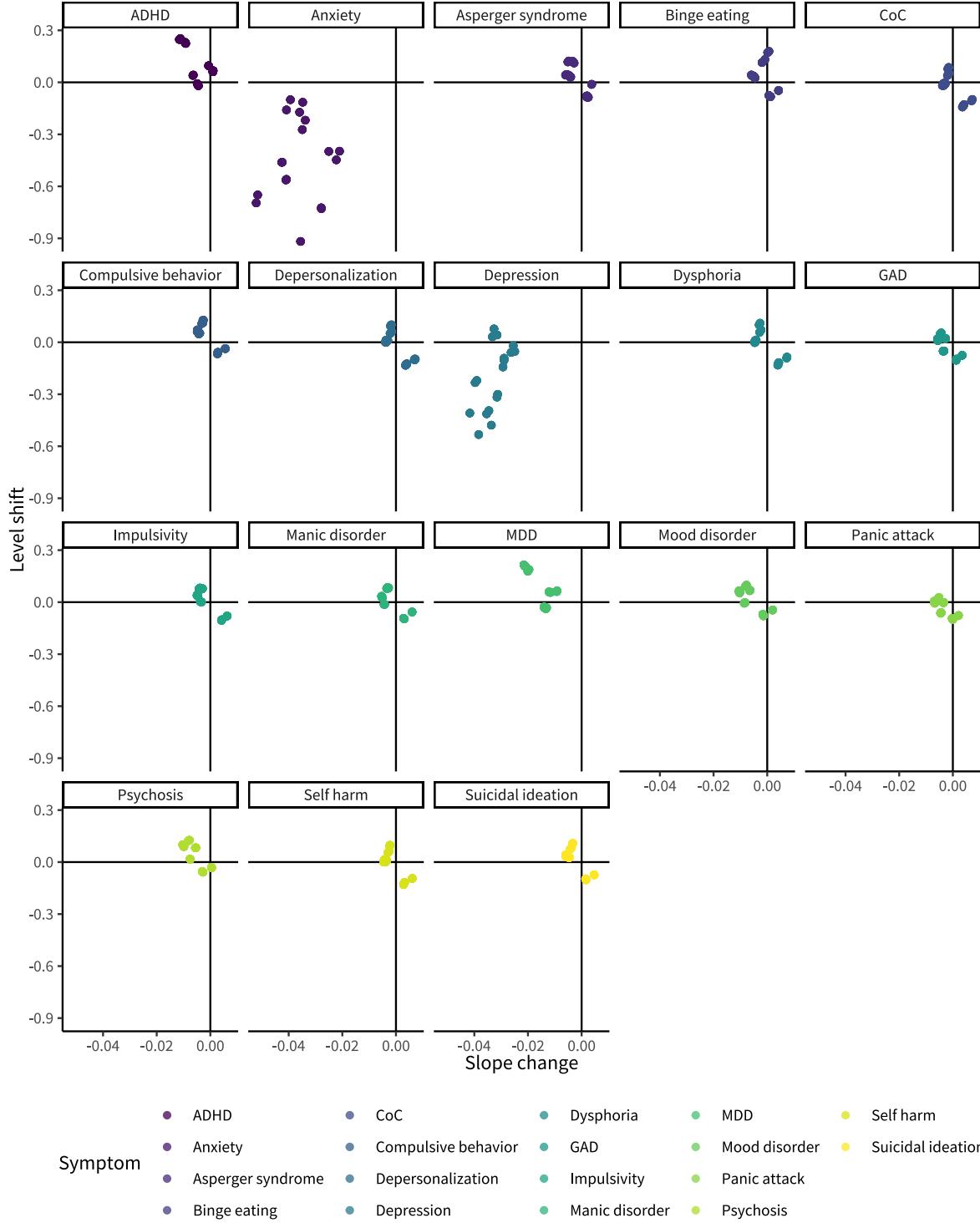


Figure 20: Controlled interrupted time series effect estimates by mental health related symptom for each model specification combination in multiverse analysis. Each point presents the effect estimates of a single model; for each symptom, the estimated slope change per day is shown on the x-axis, while the level shift over the post-announcement period is shown on the y-axis. ADHD: Attention deficit hyperactivity disorder. CoC: clouding of consciousness. GAD: generalized anxiety disorder. MDD: Major depressive disorder.

significant level shift estimate, all 64 models returned a negative level shift coefficient.

Turning to the subgroup analysis, I found modest evidence of effect estimates of similar magnitude comparing across countries (Figure 22). Across the most populous countries (Australia, the United Kingdom, and the United States), effect estimates were broadly consistent, with wider CIs than the ITS or CITS main analysis results due to the smaller number of observations. Negative level shifts and slope changes were more pronounced in New Zealand compared to other countries, while the level shift estimated for searches for depression in Ireland was positive; owing to the construction of the Google search density data being relative to regions, this may be due to differences in search volume intensity for depression in Ireland and New Zealand compared to other countries, and not due to a strong effect itself.

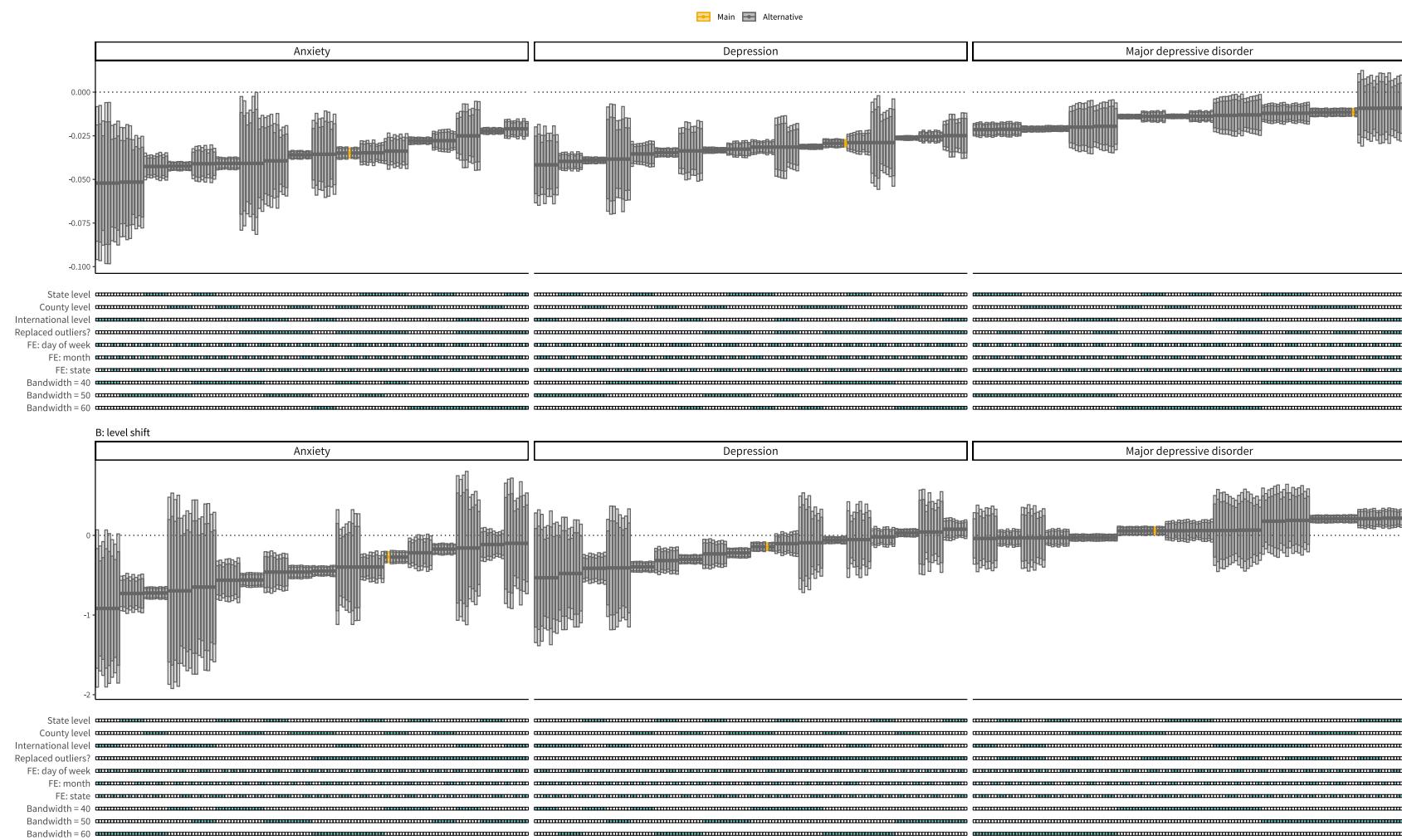


Figure 21: Specification curve depicting the CITS effect estimates and confidence intervals for search density, with panel A depicting the estimated slope change and panel B depicting the estimated level shift. Within each panel, the effect estimates across different models are depicted as circles in the upper graph; the darkly and lightly shaded regions above and below these circles correspond to 95% and 99% confidence intervals of these estimates, respectively. The dotted horizontal line depicts a null effect. The effect estimates and confidence intervals of the main specification are highlighted in orange. Below each model, a legend of shaded and unshaded boxes indicates which modeling decisions correspond to a given model, with boxes shaded teal showing active features. The three vertical columns show effect estimates by symptom. From left to right, these are anxiety, depression, and major depressive disorder. CITS: controlled interrupted time series. FE: fixed effects.

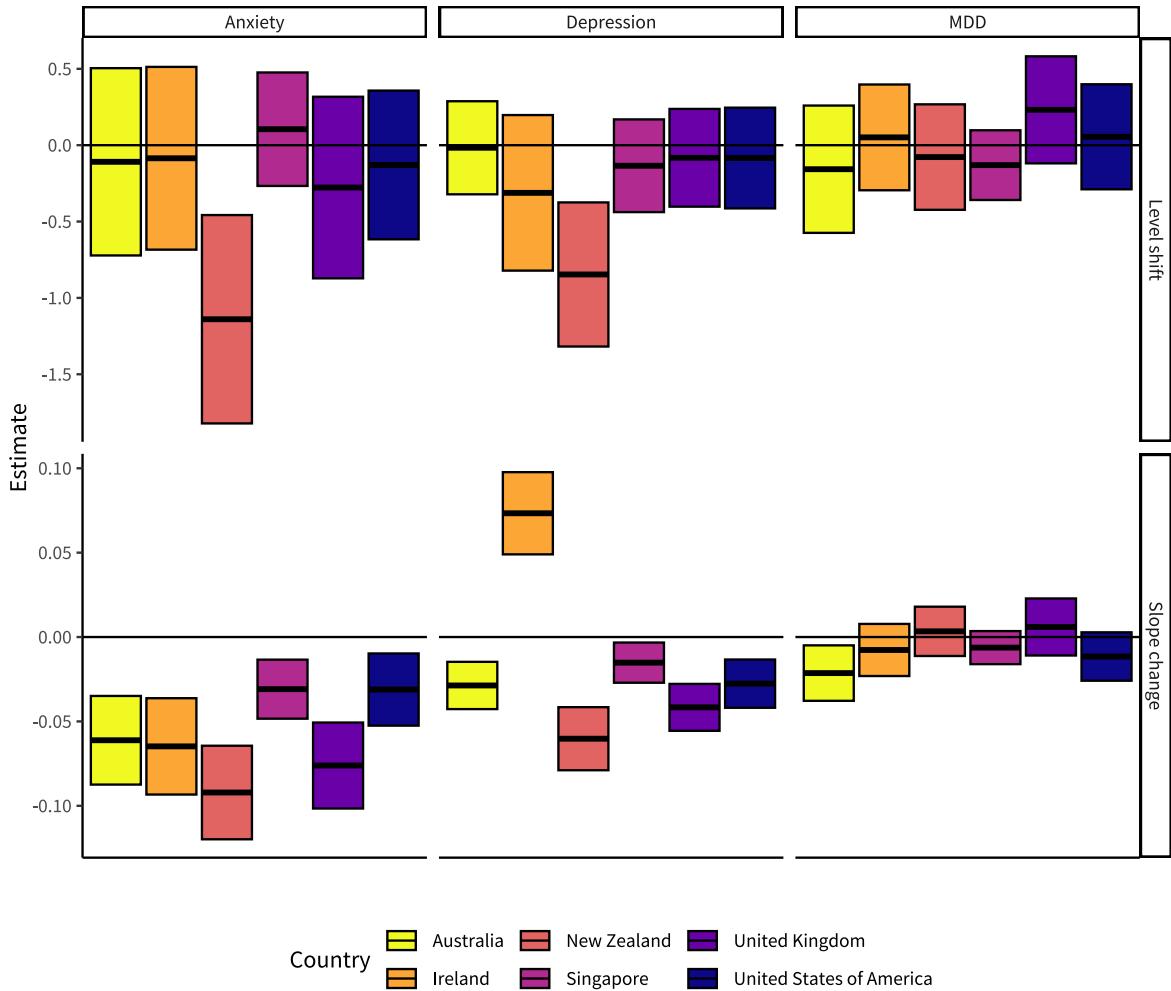


Figure 22: Controlled interrupted time series estimates of changes in search density by mental health related symptom, reported across six countries (Australia, Ireland, New Zealand, Singapore, the United Kingdom, and the United States). The top panel reports estimates of associated level shift and the lower panel estimates of the associated slope change. Estimates are represented as solid black lines, with the shaded regions above and below the lines showing the 95% confidence intervals. The solid black line across all panels reflects a null effect. MDD: Major depressive disorder.

Results from the analysis comparing red and blue states and counties showed broad consistency in both slope changes and level shifts for searches for anxiety, depression, and MDD as found in the main analysis (Figure 23). This was particularly observed in the analysis of U.S. state-level data, where confidence intervals for the CITS effect estimates were statistically equivalent across red and blue states. In the county-level analysis, however, I observed larger immediate and sustained declines

in searches for depression among red counties than blue ones, with minor overlap in confidence intervals. The observed slope change for searches related to depression among red counties was -0.033 percentage points per day ($p < 0.0001$, 99% CI: -0.036 – -0.030), compared to -0.025 percentage points per day ($p < 0.0001$, 99% CI: -0.030 – -0.021) for blue counties. Similarly, a more pronounced level shift was observed in red counties than blue ones, -0.225 percentage points ($p < 0.0001$, 99% CI: -0.289 – -0.161) versus -0.105 percentage points ($p = 0.008$, 99% CI: -0.208 – -0.003), respectively.

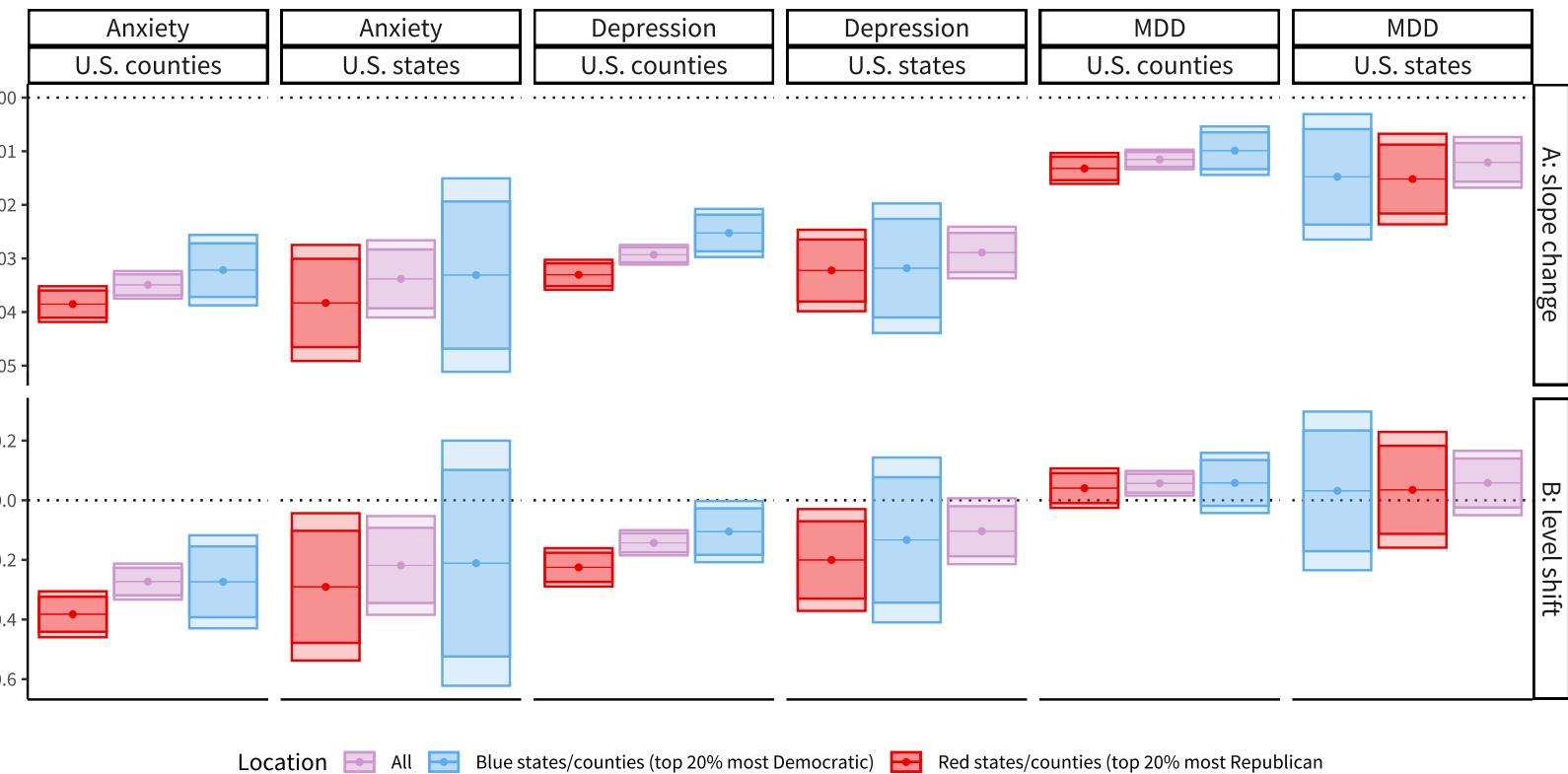


Figure 23: CITS effect estimates and confidence intervals per symptom, region, and predominant political ideology. Panel A depicts the estimated slope change and panel B the estimated level shift. The vertical panels show CITS effect estimates by mental health symptom (from left to right: anxiety, depression, and major depressive disorder); for each symptom, estimates are separately reported using county- and state-level data. For a given symptom and region, three CITS estimates are reported: one estimated from a sample of all counties or states (shown in purple), one conducted solely among the most Democratic counties or states (by 2020 presidential election vote share, shown in blue), and one among the most Republican counties or states (shown in red). Within each panel, the effect estimates across different models are depicted as points on a horizontal bar; the darkly and lightly shaded regions above and below these circles correspond to 95% and 99% confidence intervals of these estimates, respectively. The dotted horizontal line in each panel depicts a null effect. CITS: controlled interrupted time series. U.S.: United States.

3.4 Discussion

This study evaluated whether two contemporary announcements of COVID-19 vaccine safety and efficacy data on November 9th and November 16th, 2020 were associated with changes in health-related Google search density related to mental health symptoms. Using search data from U.S. counties, states, and international trends, I applied ITS and CITS modeling approaches to investigate possible associations between these announcements and search density changes. I found evidence of statistically significant immediate and sustained declines in searches for anxiety, depression, and major depressive disorder throughout the 40 days following these announcements. The declines were relatively large compared to changes in other symptoms, both physical and mental, and a multiverse analysis indicated that the findings were robust to alternative specifications.

To interpret these observed changes as reactions to the vaccine safety and efficacy announcements, it is important to evaluate whether they may be responses to other contemporary events. I highlight two potential alternatives that coincided with the period under study: the 2020 U.S. presidential election on November 3rd and the observance of the Thanksgiving holiday in the United States on November 26th. While it is possible that the estimates encompass impacts from these events, data from the subgroup analysis lends support for the interpretation that these alternatives are insufficient to explain the observed declines in search trends for anxiety, depression, and MDD.

With respect to the U.S. presidential election, I would anticipate any post-election decline in mental health related symptoms to be concentrated in the United States, given its domestic importance and the political fervor that surrounded it. Similarly, I would expect that impacts of the Thanksgiving holiday would be unique to the U.S., as it is not celebrated by the other nations in the sample and there were no other national holidays observed by those nations at the same time (with the exception of Singapore's observance of Deepavali on November 14th).

In the subgroup analysis comparing Australia, Ireland, New Zealand, Singapore, the United

Kingdom, and the United States, I did not observe evidence of U.S.-specific effects, with the analysis showing consistent declines in searches related to anxiety and depression across all countries (though these differed in degree). Furthermore, the estimated declines in search density in Australia and the United Kingdom—which, along with the U.S., are the most populous nations in the sample—were greater than that of the U.S. for these two symptom searches, providing additional counterevidence to these alternative explanations.

Further countering the explanation that observed declines in search trends for mental health symptoms were due to the U.S. presidential election are the results from the subgroup analysis comparing blue and red states/counties. If voters expressed relief following the election if their candidate was the winner, a greater decline in searches related to anxiety and depression in states and counties would be expected in those that more heavily voted for Joe Biden, the Democratic candidate and subsequent President-elect, than for former President Donald Trump, the Republican candidate. This gradient would also echo the hypothesis that, given findings that political ideology may affect receptiveness to vaccination, the announcement of vaccine safety and efficacy would have had a less pronounced effect among conservative voters compared to liberal ones. Instead, I observed the opposite: among the counties that most heavily voted for the Republican candidate, the estimated declines in search density for anxiety and depression were larger than in those that most heavily voted Democrat. I did, however, observe broad similarities in the confidence intervals of these estimates, such that I did not rule out the possibility that the effects were the same across red and blue counties. However, even this finding would be striking, giving the enduring political controversy over vaccination in the U.S.; while subsequent attitudes towards vaccination may show an ideological split by political affiliation, the findings—if taken as a reasonable reflection of individual attitudes—suggest that whatever relief the vaccine announcements brought was shared across the aisle.

These findings should be interpreted with some limitations in mind. First, the aggregated and anonymized nature of the data imposes a constraint to the interpretations, as it was not possible to identify whether individual political ideologies were correlated with changes in search trends. Instead, I relied on population aggregates that reflect political orientation (i.e., vote share by county and state) as a proxy, focusing on the 20% most Democrat and Republican-voting areas to strengthen the plausibility of this proxy. In addition, the use of Google search density as a proxy for population mental health could not be directly validated in the study, as the search data was anonymized and aggregated. While this is an important limitation, prior work has found a strong correlation between searches for anxiety and depression and U.S. population survey responses for receiving therapy, receiving medication for mental health disorders, and having unmet mental health needs.¹²⁸ Given the paucity of high frequency population mental health data, Google search density data offered a unique opportunity to investigate the immediate and sustained impacts of vaccine safety and efficacy announcements with an aggregated measures that may be linked with subjective well-being and care seeking.

Despite these limitations, the findings suggest that the announcement of COVID-19 vaccine safety and efficacy led to a robust and sustained reduction in Google search density for anxiety and depression, relative to search density prior to the announcements and to searches for other symptoms. If symptom search density echoes population health, the results would indicate that these announcements led to an improvement in mental health, an improvement observed across countries and predominant political party inclination. These findings underscore the importance of timely and transparent communication and highlight the potential application of high frequency internet search data for population mental health surveillance.

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3.5.1 Funding statement

This study received no funding.

3.5.2 Declaration of interests

I declare no competing interests.

3.5.3 Data sharing statement

All codes used for the analysis in this article are available on GitHub (https://github.com/darias5/mh_google_search_trends).

Conclusion

In this dissertation, I investigated different quantitative facets of the global burden of mental disorders, a burden that is widespread,^{2,3} growing,⁷ and largely unmet.^{9,10}

In Chapter 1, we examined how the global burden is defined, and we proposed an estimation approach to more comprehensively reflect morbidity and loss of life due to suicide and premature mortality attributable to mental disorders. After applying this composite estimation approach to the most recently available estimates from the Global Burden of Disease study, we found that approximately one in 6 disability-adjusted life years (approximately 16%) were due to mental disorders in 2019. We then applied a value of a statistical life year approach to estimate the associated global economic burden. Our findings suggest staggering losses: after accounting for premature mortality and other sources of morbidity associated with mental disorders, global losses were estimated to approximate 4.7 trillion USD in 2019. The magnitude of these findings underscores the global scale of impact that mental disorders have and highlights the urgency for research and action to support mental health worldwide.

In Chapter 2, we examined how this global burden might be shifting with changes in climate by analyzing health system data in Madagascar, a country with little to no mental health surveillance data and high vulnerability to climate change. We obtained data on monthly counts of mental health related visits reported by 3,413 facilities in Madagascar from 2010 to 2020. We then geolocated these facilities and obtained meteorologic data on climate conditions to examine the impact of three climate change exposures—temperature, soil moisture, and duration of cyclones and tropical storms. We found that monthly mental health related visits declined as temperature increased, particularly in the central highlands, where cooler temperatures were more prevalent; conversely, higher grades of soil moisture were associated with greater mental health visits with a lag of approximately three months, an increase found primarily in regions associated with higher flood risk in Madagascar. Our

findings illustrate potential heterogeneity in how changing climate conditions may impact mental health needs, and our work demonstrates how routine health system data may be leveraged to address data gaps in health surveillance, particularly in resource-constrained settings.

In Chapter 3, I examined how search data for health symptoms could, in the absence of high frequency surveillance data, provide insight into changes in population mental health during the COVID-19 pandemic. I obtained Google search data from U.S. counties, states, and international trends for over 400 symptoms and used these data to study the immediate and sustained impacts of announcements of the development of safe and effective COVID-19 vaccines in November 2020. I found that searches for anxiety, depression, and major depressive disorder significantly fell after these announcements, and that this decline continued throughout the subsequent weeks. Furthermore, despite the subsequent (and ongoing) politicization of COVID-19 vaccines in the United States, I observed consistency in search density declines for mental health symptoms across red and blue states/counties. The findings speak to the importance of timely and transparent communication in public health, as well as to the potential use of internet search data to investigate changes in population mental health that may be difficult to detect without high frequency data.

These papers add to a growing understanding of the tremendous scale of mental health needs worldwide. The magnitude of this burden has galvanized a global movement and a call to action for greater investment and prioritization for mental health.¹⁴⁴ This movement has emphasized the importance of investing in mental health as a means of promoting sustainable development, human rights, and social inclusion.⁷

To respond to this burden, health systems will need to be mindful of factors beyond the traditional extent of mental health services and consider mental health within a background of broader contextual challenges. As seen in Chapters 2 and 3, changes in climate and the course of the COVID-19 pandemic highlight the importance of considering the connections between mental

health and other issues in public health. Insofar as these challenges may exacerbate one another and strengthen vulnerabilities and inequities in health, responding to them in concert—and addressing the mental health needs of populations facing new and evolving stressors—may be key in overcoming them and fostering resiliency. This will require global, multisectoral action across countries at all economic levels, coupled with a substantive increase in financial resources dedicated to mental health.

Moreover, health systems and global health research will need to develop new means of dealing with the current limitations in the measurement of population mental health. As discussed in Chapter 1, traditional approaches to estimating the global burden of mental disorders may not capture its true scale, contributing to a lack of perceived importance of mental health to human well-being. This perception remains unchallenged, in part, due to the lack of detailed epidemiological data on the prevalence and distribution of mental disorders, a challenge that further constrains mental health research. As demonstrated by Chapters 2 and 3, innovative uses of health system and internet search data may help in overcoming this constraint but come with limitations of their own.

While this dissertation has underscored that the burden of mental disorders is complex in nature and vast in scope, the challenges this burden poses are not insurmountable. By measuring and understanding the mental health needs of populations, and by addressing these needs within a broader context of societal challenges, health systems may more effectively respond to this challenge, bringing the world closer to parity between mental health and physical health. Through a global effort to address this essential facet of human wellbeing, millions of individuals may be helped to achieve their full potential, strengthen resilience, and obtain access to the care they need to flourish.

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Supplementary materials

Appendix 1

Table S1.1: The global economic burden of mental disorders, by year and approach, calculated by Bloom and colleagues and adjusted to 2019 USD using gross domestic product deflator adjustment. Estimates are in trillions. DALY: disability-adjusted life year. GDP: gross domestic product. VSL: value of a statistical life.

Year	Cost of illness (COI)			Value of lost output (VLO) 19.09*	Value of losses using VSL approach †
	Direct costs	Indirect costs	Total		
2010	0.96	1.96	2.92		1.57 4.72
2030	2.34	4.74	7.08		2.92 8.75
Average	1.50	3.05	4.55		2.14 6.42

* Annual VLO estimates are not reported by disease category. The estimate of VLO is the total for the range 2010-2030 for mental disorders.

† Authors' calculations based on Bloom and colleagues.

Table S1.2 The economic value of mental disorder losses, using VSL approach, by year and monetary value assigned to one DALY. Authors' calculations based on Bloom and colleagues and adjusted to 2019 USD using gross domestic product deflator adjustment. Estimates are in trillions.

World Bank income group	1 DALY=		1 DALY=	
	1x GDP per capita		3x GDP per capita	
	2010	2030	2010	2030
High-income	1.02	1.32	3.05	3.97
Upper-middle-income	0.35	1.18	1.05	3.53
Lower-middle-income	0.17	0.36	0.50	1.09
Low-income	0.04	0.07	0.11	0.22
Global	1.57	2.92	4.72	8.75

DALY: disability-adjusted life year. VSL: value of a statistical life. GDP: gross domestic product.

Table S1.3: Hierarchical classification of mental disorders in the Global Burden of Disease (GBD) 2019 study.

Level 1	Level 2	Level 3	Level 4
Non-communicable diseases			
	Mental disorders		
		Schizophrenia	
		Depressive disorders	Major depressive disorder Dysthymia
		Bipolar disorder	
		Anxiety disorders	
		Eating disorders	Anorexia nervosa Bulimia nervosa
		Autism spectrum disorders	
		Attention-deficit/hyperactivity disorder	
		Conduct disorder	
		Idiopathic developmental intellectual disability	
		Other mental disorders	
Not classified as “mental disorders” under GBD 2019			
	Substance use disorders		
		Alcohol use disorders	Opioid use disorders Cocaine use disorders Amphetamine use disorders
		Drug use disorders	Cannabis use disorders Other drug use disorders
	Neurological disorders		
		Alzheimer's disease and other dementias	
		Parkinson's disease	
		Idiopathic epilepsy	
		Multiple sclerosis	
		Motor neuron disease	
		Headache disorders	Migraine Tension-type headache
		Other neurological disorders	
Musculoskeletal disorders			
Injuries			
	Self-harm and interpersonal violence		
		Self-harm	Self-harm by firearm Self-harm by other specified means

Table S1.4: Years lived with disability (YLDs) attributable to mental disorders as totals (millions) and percentages of overall burden, by World Bank income group classification and GBD region, under three estimation approaches.

	Original approach						Reallocation approach						Composite approach						
	YLDs			% of burden			YLDs			% of burden			YLDs			% of burden			
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	
Global	125.3	93.0	163.2	14.6	14.5	14.7	247.2	140.2	401.0	28.7	21.9	36.2	247.2	140.2	401.0	28.7	21.9	36.2	
High income	24.5	18.1	32.0	14.1	14.0	14.3	53.9	30.7	87.5	31.1	23.7	39.2	53.9	30.7	87.5	31.1	23.7	39.2	
Upper-middle income	45.6	33.8	59.7	14.5	14.4	14.6	92.8	51.9	152.6	29.5	22.1	37.4	92.8	51.9	152.6	29.5	22.1	37.4	
Lower-middle income	44.9	33.0	58.9	14.5	14.3	14.6	83.5	45.6	138.7	26.9	19.8	34.4	83.5	45.6	138.7	26.9	19.8	34.4	
Low income	10.1	7.4	13.5	16.5	16.3	16.7	16.8	9.4	27.5	27.3	20.8	34.1	16.8	9.4	27.5	27.3	20.8	34.1	
III	East Asia	21.0	15.7	27.3	13.2	13.1	13.2	44.1	24.8	72.2	27.7	20.8	35.0	44.1	24.8	72.2	27.7	20.8	35.0
	Southeast Asia	9.1	6.7	11.9	13.4	13.5	13.6	19.5	9.9	34.2	28.9	19.9	39.0	19.5	9.9	34.2	28.9	19.9	39.0
	Oceania	0.2	0.1	0.2	13.6	13.6	13.7	0.3	0.2	0.5	26.0	18.6	34.0	0.3	0.2	0.5	26.0	18.6	34.0
	Central Asia	1.3	0.9	1.7	14.2	14.2	14.4	2.7	1.5	4.5	30.2	22.4	38.7	2.7	1.5	4.5	30.2	22.4	38.7
	Eastern Europe	3.5	2.6	4.5	12.7	12.7	12.9	8.0	4.7	12.9	29.4	23.2	36.6	8.0	4.7	12.9	29.4	23.2	36.6
	Central Europe	1.7	1.3	2.3	11.6	11.5	11.7	4.0	2.3	6.6	26.8	20.2	34.2	4.0	2.3	6.6	26.8	20.2	34.2
	Caribbean	0.8	0.6	1.0	16.7	16.4	16.9	1.4	0.8	2.2	29.2	22.2	36.6	1.4	0.8	2.2	29.2	22.2	36.6
	Central Latin America	4.1	3.0	5.4	15.8	15.5	16.0	8.0	4.4	13.2	30.6	22.8	38.9	8.0	4.4	13.2	30.6	22.8	38.9
	Tropical Latin America	5.1	3.7	6.6	18.8	18.7	19.0	9.6	5.5	15.5	35.6	27.4	44.6	9.6	5.5	15.5	35.6	27.4	44.6
	Andean Latin America	1.1	0.8	1.4	17.5	17.1	17.9	1.9	1.1	3.1	30.6	23.6	38.0	1.9	1.1	3.1	30.6	23.6	38.0
	North Africa and Middle East	10.7	7.8	14.1	19.4	19.2	19.8	18.7	10.4	30.7	34.0	25.6	43.0	18.7	10.4	30.7	34.0	25.6	43.0
	Southern Sub-Saharan Africa	1.2	0.9	1.6	14.1	13.9	14.5	2.4	1.4	3.8	27.1	20.9	33.6	2.4	1.4	3.8	27.1	20.9	33.6
	Western Sub-Saharan Africa	6.7	4.9	9.0	14.5	14.4	14.7	12.2	6.5	20.7	26.3	19.0	34.0	12.2	6.5	20.7	26.3	19.0	34.0
	Central Sub-Saharan Africa	2.1	1.5	2.8	16.8	16.5	17.1	3.4	1.9	5.6	27.4	20.7	34.3	3.4	1.9	5.6	27.4	20.7	34.3
	Eastern Sub-Saharan Africa	5.8	4.2	7.7	16.5	16.2	16.8	9.4	5.5	15.0	26.6	21.1	32.5	9.4	5.5	15.0	26.6	21.1	32.5
	South Asia	28.8	21.2	37.6	14.1	14.0	14.2	52.7	29.1	86.8	25.9	19.1	32.8	52.7	29.1	86.8	25.9	19.1	32.8
	Southern Latin America	1.3	0.9	1.6	16.5	16.3	16.7	2.4	1.4	3.8	31.2	24.3	38.6	2.4	1.4	3.8	31.2	24.3	38.6
	Western Europe	9.4	7.0	12.4	15.4	15.3	15.6	19.4	10.9	31.9	31.7	24.0	40.4	19.4	10.9	31.9	31.7	24.0	40.4
	High-income North America	8.0	6.0	10.4	13.7	13.6	13.9	19.2	11.2	30.5	33.0	25.6	41.0	19.2	11.2	30.5	33.0	25.6	41.0
	Australasia	0.7	0.5	0.9	17.7	17.5	18.0	1.3	0.8	2.0	32.6	26.2	39.3	1.3	0.8	2.0	32.6	26.2	39.3
	High-income Asia Pacific	2.7	2.0	3.5	10.9	10.8	11.0	6.4	3.6	10.5	25.8	19.6	33.0	6.4	3.6	10.5	25.8	19.6	33.0

Table S1.5: Years of life lost (YLLs) attributable to mental disorders as totals (millions) and percentages of overall burden, by World Bank income group classification and GBD region, under three estimation approaches.

	Original approach						Reallocation approach						Composite approach					
	YLLs			% of burden			YLLs			% of burden			YLLs			% of burden		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
Global	-	-	-	-	-	-	74.0	55.0	108.6	4.4	3.5	6.0	170.5	136.5	207.3	10.2	8.7	11.4
High income	-	-	-	-	-	-	20.4	14.3	31.9	10.6	7.7	15.7	27.1	22.0	32.8	14.0	11.9	16.1
Upper-middle income	-	-	-	-	-	-	24.7	15.9	41.5	4.9	3.6	7.2	63.8	47.4	83.5	12.7	10.8	14.5
Lower-middle income	-	-	-	-	-	-	25.3	17.8	37.1	3.4	2.8	4.4	63.9	44.6	86.9	8.7	6.9	10.2
Low income	-	-	-	-	-	-	3.5	2.2	5.6	1.5	1.1	1.9	15.5	10.4	22.5	6.5	5.2	7.8
East Asia	-	-	-	-	-	-	11.7	7.0	20.9	4.9	3.4	7.7	28.5	20.8	37.6	12.0	10.1	13.8
Southeast Asia	-	-	-	-	-	-	3.8	2.2	6.5	2.9	2.0	4.3	12.8	8.8	17.8	9.8	8.0	11.7
Oceania	-	-	-	-	-	-	0.1	0.0	0.1	1.7	1.2	2.2	0.3	0.2	0.5	8.2	6.6	9.9
Central Asia	-	-	-	-	-	-	1.1	0.8	1.5	5.4	4.6	6.4	2.0	1.5	2.7	10.2	8.6	11.9
Eastern Europe	-	-	-	-	-	-	5.4	4.0	7.8	8.8	7.4	11.1	8.1	6.0	10.6	13.1	11.0	15.1
Central Europe	-	-	-	-	-	-	1.7	1.1	2.9	6.7	5.0	9.6	2.8	1.9	3.9	10.9	9.2	12.7
Caribbean	-	-	-	-	-	-	0.4	0.2	0.6	3.8	2.8	5.2	1.3	0.9	1.9	13.0	10.8	15.2
Central Latin America	-	-	-	-	-	-	2.1	1.3	3.4	5.1	4.0	6.9	6.2	4.4	8.6	15.3	13.1	17.6
Tropical Latin America	-	-	-	-	-	-	2.0	1.4	3.2	5.0	3.7	7.6	7.4	6.2	8.6	18.3	16.1	20.5
Andean Latin America	-	-	-	-	-	-	0.4	0.2	0.7	4.6	3.2	6.3	1.3	0.8	1.9	13.6	11.4	16.0
North Africa and Middle East	-	-	-	-	-	-	2.8	1.7	4.9	3.5	2.5	5.2	12.6	8.9	17.4	15.9	13.5	18.4
Southern Sub-Saharan Africa	-	-	-	-	-	-	0.8	0.6	1.2	2.8	2.2	3.6	2.3	1.7	3.1	7.9	6.5	9.3
Western Sub-Saharan Africa	-	-	-	-	-	-	2.5	1.5	4.1	1.1	0.8	1.6	8.6	5.4	12.8	4.0	3.0	5.0
Central Sub-Saharan Africa	-	-	-	-	-	-	0.7	0.5	1.1	1.6	1.2	2.0	2.9	1.9	4.3	6.5	5.0	8.0
Eastern Sub-Saharan Africa	-	-	-	-	-	-	1.9	1.3	3.0	1.5	1.2	1.9	6.4	4.4	9.2	4.9	3.9	5.9
South Asia	-	-	-	-	-	-	18.0	13.3	25.3	4.2	3.5	5.3	43.3	30.8	57.4	10.1	8.1	12.0
Southern Latin America	-	-	-	-	-	-	0.7	0.5	1.0	6.5	5.0	9.5	1.5	1.2	1.7	13.8	11.9	15.6
Western Europe	-	-	-	-	-	-	6.1	4.0	10.4	9.4	6.1	15.6	9.1	7.5	10.7	13.8	11.7	16.0
High-income North America	-	-	-	-	-	-	7.9	6.5	10.6	12.6	10.5	16.8	9.8	8.3	11.2	15.5	13.3	17.7
Australasia	-	-	-	-	-	-	0.4	0.3	0.6	11.7	8.5	17.7	0.6	0.5	0.7	16.8	14.4	19.2
High-income Asia Pacific	-	-	-	-	-	-	3.4	1.9	6.0	13.5	7.7	23.2	2.7	2.2	3.2	10.6	8.7	12.5

Table S1.6: Deaths attributable to mental disorders as totals (millions) and percentages of overall burden, by World Bank income classification and GBD region, under three estimation approaches

	Original approach						Reallocation approach						Composite approach					
	Deaths			% of burden			Deaths			% of burden			Deaths			% of burden		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
Global	-	-	-	-	-	-	3.2	1.8	5.9	5.6	3.3	9.9	5.9	4.7	7.1	10.4	8.8	12.0
High income	-	-	-	-	-	-	1.1	0.6	2.2	10.2	5.3	19.1	1.4	1.1	1.7	12.3	10.3	14.3
Upper-middle income	-	-	-	-	-	-	1.1	0.6	2.3	5.4	3.1	9.6	2.3	1.7	3.0	11.1	9.3	12.8
Lower-middle income	-	-	-	-	-	-	0.8	0.5	1.4	3.9	2.7	6.2	1.9	1.3	2.6	9.6	7.7	11.4
Low income	-	-	-	-	-	-	0.1	0.1	0.2	2.4	1.5	3.8	0.4	0.2	0.5	7.7	6.2	9.3
East Asia	-	-	-	-	-	-	0.6	0.3	1.2	5.3	3.0	9.4	1.2	0.9	1.5	10.5	8.8	12.2
Southeast Asia	-	-	-	-	-	-	0.2	0.1	0.3	3.8	2.0	6.8	0.4	0.3	0.6	9.2	7.5	11.0
Oceania	-	-	-	-	-	-	0.0	0.0	0.0	2.1	1.4	3.1	0.0	0.0	0.0	8.7	7.1	10.4
Central Asia	-	-	-	-	-	-	0.0	0.0	0.1	4.7	3.4	6.9	0.1	0.0	0.1	9.6	8.0	11.2
Eastern Europe	-	-	-	-	-	-	0.2	0.1	0.3	7.1	4.9	11.2	0.3	0.2	0.4	11.2	9.4	13.0
Central Europe	-	-	-	-	-	-	0.1	0.0	0.2	6.6	3.7	11.4	0.1	0.1	0.2	9.9	8.2	11.5
Caribbean	-	-	-	-	-	-	0.0	0.0	0.0	5.2	3.1	8.4	0.0	0.0	0.1	12.7	10.6	15.0
Central Latin America	-	-	-	-	-	-	0.1	0.0	0.2	6.4	3.6	10.8	0.2	0.1	0.2	12.6	10.6	14.8
Tropical Latin America	-	-	-	-	-	-	0.1	0.0	0.2	6.5	3.5	12.5	0.2	0.2	0.3	15.5	13.4	17.7
Andean Latin America	-	-	-	-	-	-	0.0	0.0	0.0	6.1	3.4	10.3	0.0	0.0	0.1	12.1	10.0	14.3
North Africa and Middle East	-	-	-	-	-	-	0.1	0.1	0.3	4.4	2.4	8.0	0.4	0.3	0.5	14.3	11.9	16.7
Southern Sub-Saharan Africa	-	-	-	-	-	-	0.0	0.0	0.0	3.3	2.1	5.3	0.1	0.0	0.1	8.0	6.6	9.5
Western Sub-Saharan Africa	-	-	-	-	-	-	0.1	0.0	0.2	2.2	1.3	3.5	0.2	0.1	0.3	5.1	3.9	6.3
Central Sub-Saharan Africa	-	-	-	-	-	-	0.0	0.0	0.0	2.4	1.6	3.5	0.1	0.0	0.1	7.4	5.8	9.1
Eastern Sub-Saharan Africa	-	-	-	-	-	-	0.1	0.0	0.1	2.4	1.6	3.8	0.2	0.1	0.2	6.0	4.8	7.2
South Asia	-	-	-	-	-	-	0.5	0.3	0.9	4.3	3.0	6.5	1.3	0.9	1.7	10.6	8.4	12.5
Southern Latin America	-	-	-	-	-	-	0.0	0.0	0.1	6.7	3.7	12.8	0.1	0.0	0.1	11.6	9.8	13.3
Western Europe	-	-	-	-	-	-	0.4	0.2	0.8	9.5	4.6	19.2	0.5	0.4	0.6	12.7	10.6	14.8
High-income North America	-	-	-	-	-	-	0.3	0.2	0.6	10.4	6.4	17.8	0.4	0.4	0.5	13.7	11.7	15.8
Australasia	-	-	-	-	-	-	0.0	0.0	0.0	10.6	5.5	20.6	0.0	0.0	0.0	14.9	12.6	17.3
High-income Asia Pacific	-	-	-	-	-	-	0.2	0.1	0.5	14.3	6.1	29.2	0.2	0.1	0.2	9.0	7.3	10.7

Table S1.7: The global economic burden associated with premature mortality and morbidity from mental disorders, by estimation approach and value per DALY, using alternative valuations. Dollar amounts are in trillions.

<i>Panel A: Using values per DALY of \$1,000 and \$5,000 (USD 2019)</i>									
Value per DALY (USD, 2019)	Original approach			Reallocation approach			Composite approach		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
\$1,000	0.13	0.09	0.16	0.32	0.20	0.51	0.42	0.28	0.61
\$5,000	0.63	0.46	0.82	1.61	0.99	2.53	2.09	1.38	3.04

<i>Panel B: Using GDP per capita, PPP-adjusted, per DALY (international dollars, 2019)</i>									
Value per DALY (International dollar, 2019)	Original approach			Reallocation approach			Composite approach		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
1x GDP PPP/capita	2.18	1.62	2.84	5.60	3.46	8.80	7.28	4.82	10.60
3x GDP PPP/capita	6.55	4.86	8.53	16.79	10.38	26.41	21.84	14.47	31.80

DALY: disability-adjusted life year. USD: United States dollar. GDP: gross domestic product. PPP: purchasing power parity.

Table S1.8: The economic burden associated with premature mortality and morbidity from mental disorders, by estimation approach and value per DALY, using alternative valuations and by World Bank income classification and GBD region. Dollar amounts are in trillions.

Panel A: Using \$1,000 per DALY (USD 2019)										
	Original approach			2016 reallocation approach			Composite approach			
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	
Global	0.13	0.09	0.16	0.32	0.20	0.51	0.42	0.28	0.61	
High income	0.02	0.02	0.03	0.07	0.05	0.12	0.08	0.05	0.12	
Upper-middle income	0.05	0.03	0.06	0.12	0.07	0.19	0.16	0.10	0.24	
Lower-middle income	0.04	0.03	0.06	0.11	0.06	0.17	0.15	0.09	0.23	
Low income	0.01	0.01	0.01	0.02	0.01	0.03	0.03	0.02	0.05	
East Asia	0.02	0.02	0.03	0.06	0.03	0.09	0.07	0.05	0.11	
Southeast Asia	0.01	0.01	0.01	0.02	0.01	0.04	0.03	0.02	0.05	
Oceania	-	-	-	-	-	-	-	-	-	
Central Asia	-	-	-	-	-	0.01	-	-	0.01	
Eastern Europe	-	-	-	0.01	0.01	0.02	0.02	0.01	0.02	
Central Europe	-	-	-	0.01	-	0.01	0.01	-	0.01	
Caribbean	-	-	-	-	-	-	-	-	-	
Central Latin America	-	-	0.01	0.01	0.01	0.02	0.01	0.01	0.02	
Tropical Latin America	0.01	-	0.01	0.01	0.01	0.02	0.02	0.01	0.02	
Andean Latin America	-	-	-	-	-	-	-	-	-	
North Africa and Middle East	0.01	0.01	0.01	0.02	0.01	0.04	0.03	0.02	0.05	
Southern Sub-Saharan Africa	-	-	-	-	-	-	-	-	0.01	
Western Sub-Saharan Africa	0.01	-	0.01	0.01	0.01	0.02	0.02	0.01	0.03	
Central Sub-Saharan Africa	-	-	-	-	-	0.01	0.01	-	0.01	
Eastern Sub-Saharan Africa	0.01	-	0.01	0.01	0.01	0.02	0.02	0.01	0.02	
South Asia	0.03	0.02	0.04	0.07	0.04	0.11	0.10	0.06	0.14	
Southern Latin America	-	-	-	-	-	-	-	-	0.01	
Western Europe	0.01	0.01	0.01	0.03	0.02	0.04	0.03	0.02	0.04	
High-income North America	0.01	0.01	0.01	0.03	0.02	0.04	0.03	0.02	0.04	
Australasia	-	-	-	-	-	-	-	-	-	
High-income Asia Pacific	-	-	-	0.01	0.01	0.02	0.01	0.01	0.01	

Panel B: Using \$5,000 per DALY (USD 2019)

	Original approach			2016 reallocation approach			Composite approach		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
	Global	0.63	0.46	0.82	1.61	0.99	2.53	2.09	1.38
High income	0.12	0.09	0.16	0.37	0.23	0.59	0.40	0.26	0.60
Upper-middle income	0.23	0.17	0.30	0.59	0.35	0.96	0.78	0.50	1.18
Lower-middle income	0.22	0.17	0.29	0.54	0.32	0.87	0.74	0.45	1.13
Low income	0.05	0.04	0.07	0.10	0.06	0.16	0.16	0.10	0.25
East Asia	0.10	0.08	0.14	0.28	0.16	0.46	0.36	0.23	0.55
Southeast Asia	0.05	0.03	0.06	0.12	0.06	0.20	0.16	0.09	0.26
Oceania	-	-	-	-	-	-	-	-	0.01
Central Asia	0.01	-	0.01	0.02	0.01	0.03	0.02	0.01	0.04
Eastern Europe	0.02	0.01	0.02	0.07	0.05	0.10	0.08	0.05	0.12
Central Europe	0.01	0.01	0.01	0.03	0.02	0.05	0.03	0.02	0.05
Caribbean	-	-	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Central Latin America	0.02	0.02	0.03	0.05	0.03	0.08	0.07	0.04	0.11
Tropical Latin America	0.03	0.02	0.03	0.06	0.03	0.09	0.08	0.06	0.12
Andean Latin America	0.01	-	0.01	0.01	0.01	0.02	0.02	0.01	0.02
North Africa and Middle East	0.05	0.04	0.07	0.11	0.06	0.18	0.16	0.10	0.24
Southern Sub-Saharan Africa	0.01	-	0.01	0.02	0.01	0.02	0.02	0.02	0.03
Western Sub-Saharan Africa	0.03	0.02	0.04	0.07	0.04	0.12	0.10	0.06	0.17
Central Sub-Saharan Africa	0.01	0.01	0.01	0.02	0.01	0.03	0.03	0.02	0.05
Eastern Sub-Saharan Africa	0.03	0.02	0.04	0.06	0.03	0.09	0.08	0.05	0.12
South Asia	0.14	0.11	0.19	0.35	0.22	0.56	0.48	0.30	0.72
Southern Latin America	0.01	-	0.01	0.02	0.01	0.02	0.02	0.01	0.03
Western Europe	0.05	0.03	0.06	0.13	0.08	0.21	0.14	0.09	0.21
High-income North America	0.04	0.03	0.05	0.14	0.09	0.20	0.14	0.10	0.21
Australasia	-	-	-	0.01	0.01	0.01	0.01	0.01	0.01
High-income Asia Pacific	0.01	0.01	0.02	0.05	0.03	0.08	0.05	0.03	0.07

Panel C: Using \ln GDP per capita, per DALY (USD 2019)

	Original approach			2016 reallocation approach			Composite approach		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
Global	1.42	1.06	1.85	3.64	2.25	5.73	4.74	3.14	6.90
High income	1.12	0.83	1.46	3.46	2.19	5.41	3.72	2.45	5.48
Upper-middle income	0.40	0.29	0.52	1.04	0.62	1.69	1.37	0.87	2.07
Lower-middle income	0.10	0.07	0.13	0.24	0.14	0.38	0.32	0.20	0.49
Low income	0.01	-	0.01	0.01	0.01	0.02	0.02	0.01	0.03
East Asia	0.20	0.15	0.26	0.54	0.32	0.89	0.71	0.44	1.07
Southeast Asia	0.04	0.03	0.05	0.10	0.05	0.17	0.14	0.08	0.22
Oceania	-	-	-	-	-	-	-	-	-
Central Asia	0.01	-	0.01	0.02	0.01	0.02	0.02	0.01	0.03
Eastern Europe	0.03	0.02	0.04	0.13	0.09	0.20	0.16	0.10	0.23
Central Europe	0.03	0.02	0.03	0.08	0.05	0.14	0.10	0.06	0.15
Caribbean	0.01	-	0.01	0.01	0.01	0.02	0.02	0.01	0.03
Central Latin America	0.03	0.02	0.04	0.08	0.04	0.12	0.11	0.07	0.16
Tropical Latin America	0.04	0.03	0.06	0.10	0.06	0.16	0.14	0.10	0.20
Andean Latin America	0.01	-	0.01	0.01	0.01	0.02	0.02	0.01	0.03
North Africa and Middle East	0.08	0.06	0.10	0.16	0.09	0.26	0.23	0.14	0.36
Southern Sub-Saharan Africa	0.01	-	0.01	0.02	0.01	0.03	0.02	0.02	0.04
Western Sub-Saharan Africa	0.01	0.01	0.02	0.03	0.01	0.04	0.04	0.02	0.06
Central Sub-Saharan Africa	-	-	-	0.01	-	0.01	0.01	0.01	0.01
Eastern Sub-Saharan Africa	0.01	-	0.01	0.01	0.01	0.02	0.02	0.01	0.02
South Asia	0.05	0.04	0.07	0.13	0.08	0.21	0.18	0.11	0.27
Southern Latin America	0.01	0.01	0.02	0.04	0.02	0.06	0.04	0.03	0.06
Western Europe	0.40	0.29	0.52	1.07	0.64	1.76	1.20	0.77	1.79
High-income North America	0.51	0.38	0.66	1.72	1.15	2.58	1.84	1.24	2.65
Australasia	0.04	0.03	0.05	0.09	0.06	0.15	0.10	0.07	0.15
High-income Asia Pacific	0.10	0.08	0.13	0.37	0.22	0.62	0.34	0.22	0.52

Panel D: Using 3x GDP per capita, per DALY (USD 2019)

	Original approach			2016 reallocation approach			Composite approach		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
	Global	4.27	3.17	5.55	10.93	6.76	17.20	14.22	9.42
High income	3.35	2.48	4.37	10.37	6.56	16.23	11.16	7.35	16.43
Upper-middle income	1.19	0.88	1.56	3.13	1.86	5.08	4.12	2.62	6.20
Lower-middle income	0.29	0.21	0.38	0.71	0.42	1.14	0.96	0.59	1.48
Low income	0.02	0.01	0.02	0.04	0.02	0.06	0.06	0.04	0.09
East Asia	0.61	0.46	0.79	1.63	0.96	2.67	2.12	1.33	3.20
Southeast Asia	0.12	0.09	0.15	0.30	0.16	0.52	0.42	0.24	0.67
Oceania	-	-	-	-	-	0.01	0.01	-	0.01
Central Asia	0.02	0.01	0.02	0.05	0.03	0.07	0.06	0.04	0.09
Eastern Europe	0.10	0.07	0.13	0.39	0.26	0.59	0.47	0.31	0.69
Central Europe	0.08	0.06	0.10	0.25	0.15	0.41	0.30	0.18	0.46
Caribbean	0.02	0.01	0.02	0.04	0.02	0.06	0.05	0.03	0.08
Central Latin America	0.09	0.07	0.12	0.23	0.13	0.37	0.32	0.20	0.49
Tropical Latin America	0.13	0.09	0.17	0.29	0.18	0.47	0.43	0.29	0.61
Andean Latin America	0.02	0.01	0.03	0.04	0.02	0.07	0.06	0.03	0.09
North Africa and Middle East	0.24	0.17	0.31	0.48	0.27	0.78	0.69	0.43	1.07
Southern Sub-Saharan Africa	0.02	0.01	0.03	0.05	0.03	0.08	0.07	0.05	0.11
Western Sub-Saharan Africa	0.04	0.03	0.05	0.08	0.04	0.13	0.11	0.06	0.18
Central Sub-Saharan Africa	0.01	0.01	0.01	0.02	0.01	0.03	0.03	0.02	0.04
Eastern Sub-Saharan Africa	0.02	0.01	0.02	0.03	0.02	0.05	0.05	0.03	0.07
South Asia	0.16	0.12	0.21	0.40	0.25	0.63	0.55	0.34	0.82
Southern Latin America	0.04	0.03	0.06	0.11	0.07	0.17	0.13	0.09	0.19
Western Europe	1.19	0.88	1.56	3.22	1.92	5.28	3.59	2.32	5.37
High-income North America	1.52	1.14	1.97	5.17	3.44	7.75	5.52	3.72	7.95
Australasia	0.12	0.09	0.16	0.28	0.18	0.44	0.31	0.21	0.45
High-income Asia Pacific	0.31	0.23	0.40	1.12	0.65	1.86	1.03	0.66	1.57

Panel E: Using 3x GDP per capita, PPP-adjusted, per DALY (international dollars, 2019)

	Original approach			2016 reallocation approach			Composite approach		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
	Global	2.18	1.62	2.84	5.60	3.46	8.80	7.28	4.82
High income	1.27	0.94	1.66	3.88	2.44	6.11	4.22	2.76	6.23
Upper-middle income	0.78	0.58	1.02	2.05	1.23	3.33	2.70	1.71	4.06
Lower-middle income	0.31	0.23	0.40	0.75	0.45	1.20	1.02	0.63	1.56
Low income	0.02	0.01	0.02	0.04	0.02	0.06	0.06	0.03	0.09
East Asia	0.33	0.25	0.43	0.89	0.52	1.46	1.16	0.73	1.75
Southeast Asia	0.11	0.08	0.14	0.28	0.15	0.49	0.39	0.23	0.63
Oceania	-	-	-	-	-	-	-	-	-
Central Asia	0.02	0.01	0.02	0.05	0.03	0.08	0.06	0.04	0.09
Eastern Europe	0.09	0.07	0.12	0.35	0.23	0.52	0.41	0.27	0.61
Central Europe	0.05	0.04	0.07	0.18	0.11	0.29	0.21	0.13	0.32
Caribbean	0.01	-	0.01	0.02	0.01	0.02	0.02	0.01	0.04
Central Latin America	0.06	0.05	0.08	0.16	0.09	0.25	0.22	0.14	0.34
Tropical Latin America	0.08	0.06	0.10	0.17	0.10	0.28	0.25	0.17	0.36
Andean Latin America	0.01	0.01	0.02	0.03	0.02	0.04	0.04	0.02	0.06
North Africa and Middle East	0.19	0.14	0.25	0.38	0.22	0.63	0.55	0.34	0.85
Southern Sub-Saharan Africa	0.02	0.01	0.02	0.04	0.02	0.06	0.06	0.04	0.08
Western Sub-Saharan Africa	0.03	0.02	0.04	0.06	0.03	0.10	0.09	0.05	0.14
Central Sub-Saharan Africa	0.01	-	0.01	0.01	0.01	0.02	0.02	0.01	0.03
Eastern Sub-Saharan Africa	0.02	0.01	0.02	0.03	0.02	0.05	0.04	0.03	0.06
South Asia	0.18	0.13	0.24	0.45	0.27	0.70	0.61	0.38	0.91
Southern Latin America	0.03	0.02	0.04	0.07	0.05	0.12	0.09	0.06	0.13
Western Europe	0.47	0.35	0.62	1.28	0.76	2.09	1.42	0.92	2.13
High-income North America	0.51	0.38	0.66	1.73	1.15	2.60	1.85	1.25	2.67
Australasia	0.04	0.03	0.05	0.09	0.06	0.14	0.10	0.07	0.14
High-income Asia Pacific	0.12	0.09	0.15	0.43	0.25	0.71	0.40	0.25	0.60

Panel F: Using 3x GDP per capita, PPP-adjusted, per DALY (international dollars, 2019)

	Original approach			2016 reallocation approach			Composite approach		
	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound	Estimate	Lower bound	Upper bound
Global	6.55	4.86	8.53	16.79	10.38	26.41	21.84	14.47	31.80
High income	3.81	2.83	4.98	11.65	7.32	18.32	12.66	8.29	18.70
Upper-middle income	2.33	1.73	3.05	6.16	3.68	9.99	8.09	5.14	12.18
Lower-middle income	0.92	0.68	1.21	2.26	1.35	3.61	3.07	1.88	4.69
Low income	0.05	0.04	0.07	0.11	0.06	0.17	0.17	0.10	0.26
East Asia	1.00	0.75	1.30	2.67	1.57	4.38	3.47	2.18	5.24
Southeast Asia	0.33	0.24	0.43	0.85	0.45	1.47	1.17	0.68	1.89
Oceania	-	-	-	0.01	-	0.01	0.01	0.01	0.01
Central Asia	0.05	0.04	0.07	0.15	0.09	0.23	0.18	0.11	0.28
Eastern Europe	0.27	0.20	0.35	1.04	0.70	1.56	1.24	0.82	1.82
Central Europe	0.16	0.12	0.21	0.53	0.32	0.87	0.63	0.39	0.97
Caribbean	0.02	0.01	0.03	0.05	0.03	0.07	0.07	0.04	0.11
Central Latin America	0.19	0.14	0.25	0.47	0.28	0.76	0.66	0.41	1.01
Tropical Latin America	0.23	0.17	0.30	0.52	0.31	0.83	0.76	0.52	1.08
Andean Latin America	0.04	0.03	0.05	0.08	0.05	0.13	0.11	0.07	0.17
North Africa and Middle East	0.57	0.42	0.75	1.14	0.65	1.88	1.66	1.03	2.56
Southern Sub-Saharan Africa	0.05	0.03	0.06	0.12	0.07	0.18	0.17	0.11	0.25
Western Sub-Saharan Africa	0.09	0.06	0.11	0.19	0.10	0.31	0.26	0.15	0.43
Central Sub-Saharan Africa	0.02	0.01	0.03	0.04	0.02	0.06	0.06	0.04	0.09
Eastern Sub-Saharan Africa	0.05	0.03	0.06	0.09	0.05	0.14	0.12	0.08	0.19
South Asia	0.55	0.40	0.71	1.34	0.82	2.10	1.82	1.13	2.73
Southern Latin America	0.09	0.07	0.12	0.22	0.14	0.35	0.28	0.19	0.40
Western Europe	1.42	1.04	1.86	3.83	2.29	6.27	4.27	2.76	6.39
High-income North America	1.53	1.14	1.99	5.20	3.46	7.80	5.55	3.74	8.00
Australasia	0.11	0.08	0.15	0.27	0.17	0.42	0.30	0.20	0.43
High-income Asia Pacific	0.35	0.26	0.46	1.29	0.76	2.14	1.20	0.76	1.81

Appendix 2

Appendix 2.1: Health system data cleaning

Overview of health system data The health facility data used in our study were obtained from Madagascar's *Gestion du Système d'Information Sanitaire* (GESIS), a Microsoft Access electronic health management information systems database.

While primary, district, and regional referral facilities in Madagascar all reported monthly visits related to mental disorders in GESIS, case definitions varied across facilities of different levels. Disaggregated data by specific condition (e.g., depression, schizophrenia, etc.) were only reported among regional referral hospitals and university hospitals; for all other facilities, visit by type of mental health complaint were reported in aggregate (e.g., "Neuro-psychic diseases" for district hospitals).

Disaggregated data was available by age; among adults, however, disaggregated data for adults ages 25 to 59 and adults 60 years and older was only reported by primary health facilities after 2015. For all other years and all other facilities, these age categories were not separately reported. Similarly, data by sex was only reported for primary health facilities after 2015. Referrals were reported by primary health facilities and district hospitals.

A summary of GESIS data availability is provided in Table S2.1.

Table S2.1.1: Availability of disaggregated health system data by year and level of care.

GESIS data		Primary health facilities (CSB1, CSB2, FSP)		District hospitals (CHD1, CHD2)		Regional & university hospitals (CHR, CHU)		
Years of data available		2010 - 2015		2015 - 2019		2010 - 2020		
Disease data reported by subgroup available by...	Age (bullets display which categories are available)	[2010 - 2015]		<ul style="list-style-type: none"> • Neonates: 0 to 28 days • Infants: 29 days to 11 months • Toddlers: 1 to 4 years old • Children: 5 to 14 years old • Youths: 15 to 24 years old 		[2010 - 2020]		
		<ul style="list-style-type: none"> • Adults and seniors: 25 years old and older • Seniors: 60 plus 		<ul style="list-style-type: none"> • Adults: 25 to 59 • Seniors: 60 plus 		<ul style="list-style-type: none"> • Adults and seniors: 25 years old and older • Adults and seniors: 25 years old and older 		
Sex		No		Yes		No		
Mental disorders classified (in English) as... <i>(original in French)</i>		Mental illnesses & psychic disorders <i>(Affections mentales et troubles psychiques)</i>		Mental disorders <i>(Troubles mentaux)</i>		Neuro-psychic diseases <i>(Maladies neuro-psychiques)</i>		
Availability of data on...	Cases	Yes		Yes		Yes		
	Referrals	Yes		Yes		—		

After compiling the GESIS data, we translated the case definitions from French to English. The translations are provided in Table S2.2.

Table S2.2: Mental health disorders reported in GESIS, in French and English

French	English ¹
Accident vasculaire cérébral	Stroke
Accidents ischémiques et cérébraux	Ischemic & cerebral accidents
Affections mentales et troubles ...	Mental illnesses & psychic disorders
Affections musculaires et neuro-...	Muscular & neuromuscular disorders (d.c.e.)
Affections musculaires primitives	Primary muscular disorders
Amyotrophie spinale	Spinal muscular atrophy
Ataxie héréditaire	Hereditary ataxia
Autres myopathies	Other myopathies
Autres pathologies neuro-psychiatriques	Other neuro-psychiatric pathologies
Autres syndromes d'algie céphalique	Other headache syndromes
Bouffées délirantes aiguës	Short-lived psychosis
Démences	Dementias
Dépression	Depression
Dystonie	Dystonia
Encéphalopathie toxique	Toxic encephalopathy
Epilepsie	Epilepsy
Hémiplégie	Hemiplegia

Hydrocéphalie	Hydrocephalus
Hystérie	Hysteria
Maladie de Parkinson	Parkinson disease
Maladies inflammatoires du Système ...	Inflammatory diseases of the central N.S.
Maladies neuro-psychiques	Neuro-psychic diseases
Méningo-encéphalites	Meningoencephalitis
Migraine	Migraine
Myasthénie et autres affections neuro-...	Myasthenia gravis & other neuromuscular disorders
Neuropathie héréditaire et idiopathique	Hereditary & idiopathic neuropathy
Paralysie cérébrale infantile	Infantile cerebral palsy
Paraplégie et tétraplégie	Paraplegia & quadriplegia
Polynévrite et affections du Système ...	Polyneuritis & diseases of the peripheral N.S.
Polynévrite inflammatoire	Inflammatory polyneuritis
Polynévrites	Polyneuritis
Polynévrites au cours des Maladies ...	Polyneuritis (d.c.e.)
Psychoses aiguës	Acute psychoses
Schizophrénies	Schizophrenias
Sclérose en plaque	Multiple sclerosis
Tentative de suicide	Attempted suicide
Troubles anxieux et dépressifs mixtes	Mixed anxiety & depressive disorders
Troubles de l'humeur et de l'épisode ...	Mood & manic episode disorders
Troubles de la personnalités et du ...	Personality & behavioral disorders in adults
Troubles délirants chroniques	Chronic delusional disorders
Troubles liés à l'alcool	Alcohol-related disorders
Troubles liés au canabis	Cannabis-related disorders
Troubles mentaux	Mental disorders

¹d.c.e.: in or among diseases classified elsewhere. N.S.: nervous system

We then conducted exploratory data analysis to gauge data availability by condition, year, and facility level, which are reported in Tables S2.3-5. These tables show yearly cumulative visits for mental and neurological disorders, by facility level.

Among primary health facilities, we observed that the case definition for mental disorders changed during 2015, alongside the changes in GESIS that enabled disaggregated reporting by sex and greater disaggregation for data by age.

Among district hospitals, reporting of mental disorders was consistent between 2010 and 2020. Reporting of mental disorders was most detailed among regional referral hospitals (CHRRs) and university hospitals (CHUs), with visit counts reported for 40 unique conditions.

Table S2.3: Yearly cumulative visits for mental and neurological disorders reported at primary facilities

2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mental illnesses & psychic disorders (Affections mentales et ...)									
94,507	92,805	95,171	99,743	85,212	15,491	—	—	—	—
Mental disorders (Troubles mentaux)									
—	—	—	—	—	36,044	62,812	15,311	28,404	12,276

Table S2.4: Yearly cumulative visits for mental and neurological disorders reported at district hospitals

2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Neuro-psychic diseases (Maladies neuro-psychiques)										
63,952	82,474	79,358	109,818	115,324	97,968	107,578	132,872	108,488	118,132	119,122

Table S2.5: Yearly cumulative visits for mental and neurological disorders reported at regional hospitals

2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Acute psychoses (Psychoses aiguës)												
390	942	233	217	152	334	752	395	142	61	94	120	11
Alcohol-related disorders (Troubles liés à l'alcool)												
537	676	649	388	399	238	363	570	635	393	268	250	103
Attempted suicide (Tentative de suicide)												
171	174	136	145	145	107	144	215	146	125	139	104	34
Cannabis-related disorders (Troubles liés au cannabis)												
623	1,985	283	177	155	318	436	649	716	260	428	112	38
Chronic delusional disorders (Troubles délirants ...)												
584	1,637	184	177	150	59	144	153	125	85	193	100	23
Dementias (Démences)												
44	42	29	48	39	34	143	97	36	8	4	9	2
Depression (Dépression)												
595	641	584	733	843	635	628	539	462	373	333	276	87
Dystonia (Dystonie)												
683	1,206	1,321	1,253	1,407	1,899	2,227	1,776	2,211	2,430	1,908	2,370	448
Epilepsy (Epilepsie)												
2,365	2,636	2,826	4,225	4,357	3,087	1,774	1,413	1,644	1,276	1,079	862	186
Hemiplegia (Hémiplégie)												
150	189	245	121	159	122	95	109	122	248	87	39	47
Hereditary & idiopathic neuropathy (Neuropathie héréditaire ...)												
26	8	14	34	5	16	5	9	22	27	7	17	6
Hereditary ataxia (Ataxie héréditaire)												
22	0	1	2	1	188	279	101	35	2	0	6	0
Hydrocephalus (Hydrocéphalie)												
21	64	53	24	37	30	38	24	17	19	12	9	3
Hysteria (Hystérie)												
297	207	144	204	206	347	526	313	191	234	140	131	68
Infantile cerebral palsy (Paralysie cérébrale ...)												
94	106	152	236	179	428	272	287	172	352	73	44	20

Inflammatory diseases of the central nervous system (Maladies inflammatoires ...)

54	33	43	158	73	463	694	302	21	18	4	13	0
Inflammatory polyneuritis (Polynévrite inflammatoire)												
26	108	36	15	6	5	2	11	7	5	1	13	2
Ischemic & cerebral accidents (Accidents ischémiques et ...)												
70	103	116	56	99	194	1,048	440	832	516	410	509	132
Meningoencephalitis (Méningo-encéphalites)												
15	11	14	15	10	9	29	10	14	17	3	8	1
Migraine (Migraine)												
752	1,195	1,552	1,431	1,503	1,141	1,057	1,065	1,125	1,012	793	576	177
Mixed anxiety & depressive disorders (Troubles anxieux et dé...)												
222	126	476	286	186	182	152	77	225	37	62	44	45
Mood & manic episode disorders (Troubles de l'humeur et ...)												
213	80	79	121	111	158	542	334	135	66	194	56	21
Multiple sclerosis (Sclérose en plaque)												
124	30	8	12	23	20	11	12	20	7	12	13	7
Muscular & neuromuscular disorders of diseases classified elsewhere (Affections musculaires ...)												
104	45	61	101	169	86	199	200	240	404	292	206	21
Myasthenia gravis & other neuromuscular disorders (Myasthénie et autres ...)												
150	96	152	222	269	314	279	128	311	459	288	534	64
Other headache syndromes (Autres syndromes d'algie ...)												
380	700	716	671	982	1,031	285	336	304	445	284	263	33
Other myopathies (Autres myopathies)												
72	34	46	67	41	61	225	69	65	43	47	26	3
Other neuro-psychiatric pathologies (Autres pathologies neuro-...)												
1,531	1,986	1,834	2,526	1,286	1,548	1,050	2,119	2,796	2,119	1,822	1,236	288
Paraplegia & quadriplegia (Paraplégie et tétraplégie)												
32	41	39	43	44	53	62	25	44	69	30	22	4
Parkinson disease (Maladie de Parkinson)												
48	62	45	25	22	202	596	279	33	52	17	11	6
Personality & behavioral disorders in adults (Troubles de la ...)												
207	234	183	224	135	580	1,662	1,017	142	125	194	74	18
Polyneuritis & diseases of the peripheral nervous system (Polynévrite et ...)												
316	119	62	78	59	47	42	45	28	79	95	68	20

Polyneuritis (Polynévrites)														
133	69	55	78	16	25	35	38	16	18	35	34	0		
Polyneuritis in diseases classified elsewhere (Polynévrites au cours ...)														
45	14	17	24	7	21	3	4	5	61	22	2	4		
Primary muscular disorders (Affections musculaires ...)														
37	19	10	21	10	66	118	45	112	8	54	8	66		
Schizophrenias (Schizophrénies)														
662	779	649	784	1,001	1,025	341	998	1,209	430	883	182	50		
Short-lived psychosis (Bouffées délirantes aiguës)														
162	87	75	171	102	132	255	134	65	45	19	40	8		
Spinal muscular atrophy (Amyotrophie spinale)														
7	1	0	10	0	292	1,180	744	110	0	0	0	0		
Stroke (Accident vasculaire céré...)														
345	495	498	493	369	349	264	418	450	337	262	284	78		
Toxic encephalopathy (Encéphalopathie toxique)														
47	20	30	23	39	34	20	30	47	44	7	34	13		

Data cleaning approach To address heterogeneity in reporting across primary, district, and regional facilities, our analysis constructed a single, summary outcome measure: any mental or neurological disorders reported in a given month by a given facility, irrespective of age and sex. This outcome measure was constructed by grouping our count data by facility and month-year, and then summing the incidence of mental and neurological disorders reported in GESIS within groups, preventing double counting and the inclusion of referrals in the summary measure.

Visual inspect of our data showed potential outliers, which may have arisen due to data entry mistakes, synchronization errors, and other sources. To address outliers, monthly observations of the outcome were arranged separately for each facility into a unique time series. The nonparametric Friedman's super smoother regression estimator⁷⁷ was applied to each time series to identify outlier observations and replace them through linear interpolation⁷⁸. By considering outliers on a facility-

by-facility basis, the data cleaning approach preserved extreme values that may have reflected true variances in visit counts (for example, visits reported by a large, regional reference hospital) while addressing potential errors in data entry. Interpolated values were coerced to the nearest integer.

Linear interpolation ultimately only impacted 2,085 of 37,260 observations of our summary outcome measure, leaving approximately 94% of observations unadjusted.

Appendix 2.2: Health facility geocoding and validation

Overview of Madagascar's health sector In Madagascar, public health facilities can broadly be classified under four types:

- **Basic** health facilities (*centre santé de base*, or CSB)
- **District** referral hospitals (*centre hospitalier de référence de district*, or CHD/CHRD)
- **Regional** referral hospitals (*centre hospitalier de référence régionale*, or CHRR)
- **University** hospitals (*centre hospitalier universitaire*, or CHU)

According to the World Bank, there were 3,246 of these facilities operating in Madagascar in 2012.¹⁴⁵ Of these, 3,074 were CSB facilities. CSB facilities are classified as either level 1 or 2 based on population, staffing, and services provided. Facilities may be upgraded over time, such that a CSB1 facility is converted into a CSB2. At the district level, 150 CHD facilities were functional in 2012. Like CSB facilities, CHD facilities are classified as either level 1 or level 2; these facilities provide essential medical services and—in the case of CHD2 facilities—surgical care. At the regional level, 16 CHRR and 6 CHU facilities were operational in 2012, providing specialized medical and surgical care.

In addition to these public facilities, private primary health facilities (*formations sanitaires privées de base*, or FSB) are also operational and report data to the Ministère de la Santé Publique. A USAID private health sector report identified 825 FSB facilities in Madagascar operating and providing data in 2017.¹⁴⁶

Sample of health facilities The sample of health facilities in our study was obtained from health facility data from Madagascar's *Gestion du Système d'Information Sanitaire* (GESIS). While the format of outputs from GESIS varied across years and facility type, there were four variables which uniquely identified facilities.

- **Region:** The region of Madagascar that contained the facility’s catchment area. All facilities had a value for this variable.
- **District:** The district of Madagascar (2nd largest administrative unit) that contained the facility’s catchment area. Only district- and commune-level facilities had a value for this variable.
- **Commune:** The commune of Madagascar (3rd largest unit) that contained the facility’s catchment area. Only basic health facility had a value for this variable.
- **FS:** The facility type and name. The facility type would typically be identified with an acronym (e.g., CSB2, CHD1, etc.), with the facility name following thereafter. The facility name would occasionally be the same as the commune, district, or region that corresponded with the facility’s catchment area (e.g., CHRR Alaotra Mangoro). Some facilities were named for the village (*fokontany*) that they were located in. Other facilities were named for the groups that operated them (e.g., facilities named “EKAR” are operated by the *Eglisy Katôlika Apôstolika Rômanina*, or the Roman Catholic Church).

Before beginning to geolocate our sample, we began by identifying the unique facilities therein. At first pass, our sample included 3,311 uniquely named facilities. We observed, however, several instances where facilities in different regions shared the same facility name: for example, there is a CSB2 facility named “Ambalabe” in both the Sava and Atsimo Atsinanana regions, which are located at the northern and southern ends of Madagascar, respectively.

These cases indicated that identifying unique facilities would require catchment area information (as well as facility name and type) to avoid erroneously classifying unique facilities as duplicates.

Using facility name, type, and catchment area to uniquely identify facilities in our sample, we identified 3,431 unique facilities. In order to classify these facilities by type, we extracted the relevant data from the “FS” variable; in doing so, we observed slight orthographic variations in the

classification of facilities types (e.g., "CSB 1" vs. "CSB1") that required standardization.

We standardized region, district, and commune names in our sample against reference shapefiles to address variations in translation (e.g., "Atsimo" and "Sud" being the Malagasy and French words for "South"), abbreviation (e.g., "St." as an abbreviation for "Saint"), transposition (e.g., "Bevoay Beretra" transposed as "Beretra Bevoay"), accent marks (e.g., "Tovòna" vs. "Tovona"), spacing (e.g., "AmbalapaisoII" vs. "Ambalapaiso II"), separation vs. combination of names (e.g., "Tanambaovatrakaka" vs. "Tanambao Vahatrakaka"), hyphenation (e.g., "Ankiabe Salohy" and "Ankiabe-Salohy"), and spelling (e.g., "Mizilo Gare" vs. "Mizilo Gara").

A summary of the standardization changes is provided below.

Table S2.7: Standardization of district names

Name in data	Standardized name
Ambatoboeny	Ambato Boeni
Amboasary Atsimo	Amboasary-Atsimo
Ambovombe Androy	Ambovombe-Androy
Ankazoabo Atsimo	Ankazoabo
Anosibe An'Ala	Anosibe-An'ala
Antanambao Manampont	Antanambao Manampontsy
Antanambao Manampotsy	Antanambao Manampontsy
Antananarivo Atsimon	Antananarivo Atsimondrano
Antananarivo Avaradr	Antananarivo Avaradrano
Antananarivo Renivoh	Antananarivo Renivohitra
Befandriana Avaratra	Befandriana Nord
Belo Tsiribihina	Belo Sur Tsiribihina
Boriziny	Port-Berge (Boriziny-Vaovao)
Fenoarivo Atsinanana	Fenerive Est
FenoarivoBe	Fenoarivobe
Fianarantsoa II	Fianarantsoa I
lalangina	Lalangina
Mananara Avaratra	Mananara-Avaratra
Midongy Atsimo	Midongy-Atsimo
Nosy Be	Nosy-Be
Nosy Boraha	Sainte Marie
Nosy Varika	Nosy-Varika
Toliara-I	Toliary-I
Toliara-II	Toliary-II
Toliara I	Toliary-I
Toliara II	Toliary-II

Tsiombe	Tsihombe
Vohibinany	Brickaville
Vohimarina	Vohemar

Table S2.8: Standardization of district names, based on commune name

Communes	District name in data	District name, updated
Antanamalaza	Antsirabe II	Ambatolampy
Antanambao Ambary	Betafo	Mandoto
Ambalamidera	Fianarantsoa I	Isandra
Andoharanomaintso	Fianarantsoa I	Isandra
Anjoma-tsara	Fianarantsoa I	Isandra
Ankarinarivo	Fianarantsoa I	Isandra
Fanjakana	Fianarantsoa I	Isandra
Iavinomby	Fianarantsoa I	Isandra
Isorana	Fianarantsoa I	Isandra
Nasandratrony	Fianarantsoa I	Isandra
Soatanana	Fianarantsoa I	Isandra
Alakamisy Ambohimahy	Fianarantsoa I	Lalangina
Ambalakely	Fianarantsoa I	Lalangina
Ambalamahasoa	Fianarantsoa I	Lalangina
Andianjanto Est	Fianarantsoa I	Lalangina
Andrainjanto Centre	Fianarantsoa I	Lalangina
Androy	Fianarantsoa I	Lalangina
Fandravandava	Fianarantsoa I	Lalangina
Ialanidanro	Fianarantsoa I	Lalangina
Ivoamba	Fianarantsoa I	Lalangina
Mahatsinjo	Fianarantsoa I	Lalangina
Mahatsinjony	Fianarantsoa I	Lalangina
Sahambavy	Fianarantsoa I	Lalangina
Taindambo	Fianarantsoa I	Lalangina
Alakamisy Itenina	Fianarantsoa I	Vohibato
Andranomiditra	Fianarantsoa I	Vohibato
Andranovorivato	Fianarantsoa I	Vohibato
Ankaromalaza Mifanas	Fianarantsoa I	Vohibato
Ihazoara	Fianarantsoa I	Vohibato
Mahaditra	Fianarantsoa I	Vohibato
Mahasoabe	Fianarantsoa I	Vohibato
Maneva	Fianarantsoa I	Vohibato
Soaindrana	Fianarantsoa I	Vohibato
Talata Ampano	Fianarantsoa I	Vohibato
Vohibato Ouest	Fianarantsoa I	Vohibato
Vohimarina	Fianarantsoa I	Vohibato
Vohitrafeno	Fianarantsoa I	Vohibato
Andribavontsona	Port-Berge (Boriziny-Vaovao)	Analalava
Ambohimahavelona	Toliara-I	Toliary-II

Ambolofoty	Toliara-I	Toliary-II
Anakao	Toliara-I	Toliary-II
Analamisampy	Toliara-I	Toliary-II
Andranohinaly	Toliara-I	Toliary-II
Andranovory	Toliara-I	Toliary-II
Ankililoaka	Toliara-I	Toliary-II
Ankilimalinika	Toliara-I	Toliary-II
Beheloka	Toliara-I	Toliary-II
Behompy	Toliara-I	Toliary-II
Belalanda	Toliara-I	Toliary-II
Betsinjaka	Toliara-I	Toliary-II
Manombo	Toliara-I	Toliary-II
Manorofify	Toliara-I	Toliary-II
MarofotyMarofoty	Toliara-I	Toliary-II
Maromiandra	Toliara-I	Toliary-II
Miary	Toliara-I	Toliary-II
Milenaka	Toliara-I	Toliary-II
Mitsinjo	Toliara-I	Toliary-II
Soalara	Toliara-I	Toliary-II
St Augustin	Toliara-I	Toliary-II
Tsianisiha	Toliara-I	Toliary-II
Antsahavaribe	Vohemar	Sambava

Table S2.9: Standardization of commune names

Name in data	Standardized name
Alakamisy Ambohimahy	Alakamisy Ambohimaha
Ambadrika	Ambandrika
Ambalamanasy II	Ambalamanasy II
Ambalamidera	Ambalamidera II
AmbalapaisoII	Ambalapaiso II
Ambararatabe /Nord	Ambararatabe Nord
Ambarijeby Atsimo	Ambarijeby Sud
Ambatoben'anja	Ambatoben'anjavy
AmbatofisakaII	Ambatofisaka II
AmbatoharananaI	Ambatoharanana
Ambatolampy Tsimahaf	Ambatolampy
Ambatolampy Tsimahafotsy	Ambatolampy
Ambatoriha/Est	Ambatoriha Est
Ambatotsipihana	Ambatotsipihina
Ambatovala	Ambatolava
Ambatry	Ambatry Mitsinjo
Ambinanin'Andravory	Ambinanin'andravory
Ambinaninandro	Ambinanindrano
Ambinaniroa-Andonaka	Ambinaniroa
Ambodiadabo	Ambodiadabo M

Ambodiadabo Maitsokely	Ambodiadabo
Ambodiampana Lokoho	Ambodiampana
Ambodiampanana	Ambodiampana
Ambodifarihy	Ambodifarihy Fenomanana
Ambodihazambo	Ambodihazoambo
Ambodimanga I	Ambodimanga I
Ambodimanga II-B	Ambodimanga II
Ambodimotsos Atsimo	Ambodimotsos Sud
AmbodinonokaAntaratr	Ambodinonoka
Ambodirian'Isahafary	Ambodirian'i Sahafary
Ambuditandroho	Ambuditandroho
Ambohibao Atsimo	Ambohibao Sud
Ambohibary	Ambohibary Vohilena
Ambohijato Mandritsara	Mandritsara
Ambohimahavelona	Ambohimahavelona
Ambohimalaza	Ambohimalaza Miray
Ambohimàna	Ambohimana
Ambohimanga Sud	Ambohimanga Du Sud
Ambohimanjaka	Sahatsiho Ambohimanjaka
AmbohimiarinaII	Ambohimiarina II
Ambohitralalana	Ambohitralanana
Ambohitrandriamanitr	Ambohitrandriamanitra
AmbohitsaraEst	Ambohitsara Est
Ambolidibe Atsinanana	Ambolidibe Est
Amboropotsy	Amborompotsy
Ampasimadinika	Ampasimadinika Manambolo
Ampasimbajka	Ampasimboraka
Ampasimpotsy	Ampasimpotsy Sud
Ampasipotsy Gare	Ampasipotsy Gara
Ampasipotsy Madialaz	Ampasipotsy Mandialaza
Ampataka Manampaneva	Manampaneva
Ampataka Marorenny	Ampatakamarorenny
Analalaiva	Analaina
Analamitsivala	Analamitsivalana
Anbatomainty	Ambatomainty
Andanandava	Antanandava
Andianjanto Est	Andrainjato Est
Andimaka	Andimaky Manambolo
Andoharanomaintso	Andoharanomaitso
Andoharanomaintso	Andoharanomaitso
Andrainjanto Centre	Andrainjato Centre
Andranomiely	Rambolamasoandro Andranomiely
Andravola	Andravola Vohipeno
Andrebakely	Andrebakely Nord
Androndrone	Androndrone
Anjapaly	Anjampaly
Anjeke Ankilikira	Anjeky Ankilikira
Anjeva Gare	Anjeva Gara

Anjiabe	Anjiabe Ambony
Anjaiija	Anjiajia
Anjoma-tsara	Anjoma Itsara
Anjoman'Ankona	Anjoman'ankona
Ankadinondry	Ankadinondry Sakay
Ankafina	Ankafina Tsarafidy
Ankarinarivo	Ankarinarivo Manirisoa
Ankaromalaza Mifanas	Ankaromalaza Mifanasoa
Ankasakasa	Ankasakasa Tsibiray
Ankazoabo	Ankazoabo Sud
Ankazotokana I	Ankazotokana
Ankiabe Salohy	Ankiabe-Salohy
Ankiakabe-Nord	Ankiakabe Nord
Ankilimalinika	Ankilimalinike
Ankirondro	Bemarivo Ankirondro
Anontsibe	Anontsibe Centre
Anosiarivo	Anosiarivo I
Anosy Tsararafara	Anosy Tsararafa
Antalahala	Antalahala Ambonivohitra
Antanambao I	Antanambao
Antanambao Manampotsy	Antanambao Manampontsy
Antanambaon'Amberina	Antanambaon'amberina
Antananarivo I	1er Arrondissement
Antananarivo II	2e Arrondissement
Antananarivo III	3e Arrondissement
Antananarivo IV	4e Arrondissement
Antananarivo V	5e Arrondissement
Antananarivo VI	6e Arrondissement
Antanandava Nord	Antanandava
Antananivo /Haut	Antananivo Haut
Antanetibe Mahazaza	Antanetibe
Antanimora- Sud	Antanimora Atsimo
Antenina I	Antenina
Antoby	Antoby Est
Antohaboto	Antohabato
Antokorobitelo	Marovitsika Sud
Antongo	Antongo Vaovao
Antranonkarany	Antranokarany
Antsakomanondro	Antsakoamanondro
Antsapanimahazo	Antsapanimahazo
Antsirabe I	Antsirabe Afovoany Atsinanana
Antsiranana I	Diego Suarez
Antsoantany	Antsoatany
Bealampoana	Bealampona
Bealanana I	Bealanana
Beampombo I	Beampombo I
Beandrarezona I	Beandrarezona
Befandriana-Sud	Befandriana Sud

Befandriana Avaratra	Befandriana Nord
Befetra	Befeta
Befotaka	Befotaka Sud
Befotaka Avaratra	Befotaka Nord
Behera	Behara
Belafika Haut	Belafike Haut
Belambo	Belambo Firaisana
Belaoko Marovato	Belaoka Marovato
Belo sur Mer	Belo Sur Mer
Belo Tsiribihina	Belo Sur Tsiribihina
Belotsiribihina	Belo Sur Tsiribihina
Bemaneviky H	Bemaneviky Haut Sambirano
BenatoToby	Benato Toby
Beraketa	Bereketa
Berevo Ranobe	Berevo/ranobe
Beroy Sud	Beroy Atsimo
Betioky Sud	Betioky Atsimo
Betsakotsako Andrano	Betsakotsako Andranotsara
Betsimiositra	Betsimisotra
Bevoay Beretra	Beretra Bevoay
Bevonotro	Bevonotra
Efatsy Anandroza	Efatsy
Enakara Haut	Enakara-Haut
Enaniiliha	Enaniliha
Ereda	Erada
Etrotroka	Etrotroka Atsimo
Fandravandava	Fandravandava
Faux-Cap	Betanty (Faux Cap)
Fenoovo	Fenoovo-Efita
Fieferana	Fieferana
Foulpointe	Mahavelona (Foulpointe)
Ialananidro	Ialananidro
Iavinomby	Iavonomby Vohibola
Ibity	Alatsinainy Ibity
Ihaborano Namohora	Namohora Iaborano
Iloto	Menamaty Iloto
Imady	Imerina Imady
Imeritsiatosika	Imerintsiatosika
Isaka Ivondro	Isaka-Ivondro
Isaraha	Isahara
Ivatana	Vatana
Ivato Aéroport	Ivato Aeroport
Ivony	Ivony Miaramiasa
Kalalao	Ikalalao
Kianjandrakefina	Kianjandrakefina
labohazo	Iabohazo
Lavaraty Ivondro	Ivondro
Mahafasa	Mahafasa Centre

Mahajanga I	Mahajanga
Mahatsara Lefaka	Mahatsara Iefaka
Mahatsinjo	Mahatsinjony
Mahatsinjo Atsinanana	Mahatsinjo Est
Mahazina	Mahazina Ambohipierenana
Manajary Urbain	Mananjary
Manakambahiny Est	Manakambahiny Antsinanana
Manakambahiny Ouest	Manakambahiny Andrefana
Manakara(com)	Manakara
Manambotra Sud	Manambotra Atsimo
Manapatrana	Manampatrana
Mandromodromotra	Mandromondromotra
Mangarivot	Mangarivotra
Manombo	Manombo Sud
Marintampona	Maritampona
Marivorahona	Tanambao Marivorahona
Maroarivo	Maroarivo Ankazomanga
MarofotyMarofoty	Marofoty
Maromokotra-Loky	Maromokotra Loky
Marosavoa Bas	Marosavoa
Marovitsika	Marovitsika Sud
Merimandroso	Imerimandroso
Miary	Miary Ambohibola
Mitsinjo	Mitsinjo Betanimena
Mizilo Gare	Mizilo Gara
Moramanga Urbain	Moramanga
Morarano Gare	Morarano Gara
Morombe	Cu Morombe
Nagnarena	Nanarena Besakoa
Niarovana	Niarovana Marosampanana
Nosibe Masianaka	Masianaka
Onilhy	Onilahy
Port Bergé I	Port Berge
Port Bergé II	Port Berge II
Rantabe Est	Rantabe
Rantabe Sud	Rantabe
Razanaka	Vohipeno Razanaka
Sahamadio	Sahamadio Fisakana
Sahambo	Sahambano
Sahanivotry Atsimo	Sahanivotry Manandona
Sakamahily-Ouest	Sakamahily
Sakay	Tanamarina Sakay
Sakona	Sakoana
Sambava Urbain	Sambava Cu
Sarobaratra	Sarobaratra Ifanja
Soalara	Soalara Sud
St Augustin	Saint Augustin
Talata Ampano	Tatala Ampano

Talatan'Angavo	Talata Angavo
Tanakamba	Tanakambana
Tanambao Daoud	Tanambao Daoud
Tanambaovatrakaka	Tanambaovatrakaka
Tanandava-Sud	Tanandava Sud
Tanandrano	Tandrano
Taolognaro	Fort-Dauphin
Toamasina Suburbain	Toamasina Suburbaine
Tovôna	Tovona
Tsarahonenana	Tsarahonenana Sahanivotry
Tsarajomoko	Tsarajomoka
Tsaratanana	Tsaratanana I
Tsiafajavona Ankarat	Tsiafajavona Ankaratra
Tsianofâna	Tsianofâna
Tsinjoarivo	Tsinjoarivo Imanga
Tsiombe	Tsihombe
Tsiroanomadidy Ville	Tsiroanomandidy Fihaonana
Tsiroanomandidy Ville	Tsiroanomandidy Fihaonana
Vatolatsaky	Vatolatsaka
Vilihazo	Vilihazo
Vinaninony Avaratra	Vinaninony Atsimo
Vineta Andamasiny	Andamasiny Vineta
Zomabealoka	Zoma Bealoka

After standardizing facility types and catchment areas, the sample consisted of 3,415 unique facilities. This list of facilities was then manually inspected for any remaining duplicates. From reviewing this list, we observed that in the Diana region, the regional hospitals named “Hopitaly MANARA-PENITRA” and “Hopitaly Manara-Penitra Antsiranana” were duplicates, but appeared separately because the latter name contained the city the hospital is located in, Antsiranana. We standardized the names of those facilities, which resolved 2 duplicates).

The final sample of 3,413 unique facilities consisted of: 2,412 CSB facilities, including 890 CSB1s, 1,521 CSB2s, and 1 of unknown level; 792 FSP facilities; 164 district hospitals, including 52 CHD1 facilities, 42 CHD2 facilities, and 70 facilities of unknown level, and 45 regional hospitals, including 19 CHRRs, 8 CHUs, and 18 of unknown type.

Matching Approach Step 1: Matching to validated spatial inventory of public facilities in Sub-Saharan Africa

We began by gathering data from a validated spatial inventory of health facilities in Sub-Saharan Africa,⁷⁹ of which 2,625 coordinates were available for public facilities in Madagascar.

In order to systematically match facilities in our sample to facilities in the spatial inventory, we implemented an approximate string matching technique. This technique—also known as “fuzzy string searching”—is a common approach to record linkage, where information from one source (e.g., our sample) needs to be linked to data from another (e.g., the spatial inventory). As its name suggests, this techniques allows for “strings” of text to be matched approximately, rather than exactly, to corresponding patterns. In our case, this can be helpful if the facility name is spelled slightly differently in our sample versus the spatial inventory, due to typographic errors in the raw data or small orthographic variations (e.g., writing “2” as “II”, inclusion or omission of a dash, etc.). A description of how this approach can be implemented in R is available at www.R-bloggers.com.¹⁴⁷

To account for similarly named facilities located in different regions, we constructed a full, standardized name for each facility that included facility name and catchment area prior to applying our matching technique. Facility type was standardized to align with the facility types in our sample. For example, the full, standardized name for the Alakamisy Tsarazaza Health Post located in the commune of Tsarazazaa in the Fandrian district of Amoron’I Mania region would be “Alakamisy Tsarazaza Fandrian Amoron’I Mania”, with the facility classified as a CSB1 facility).

The similarity between two strings of text can be measured numerically using the Levenshtein (or edit) distance.¹⁴⁸ The Levenshtein distance between two identical strings will be zero, while strings involving a single character edit (insertions, deletions or substitutions) will involve a distance of 1.

To identify the closest matches between the full, standardized facility names in our sample and

the spatial inventory, we calculated a matrix identifying the pair-wise Levenshtein distance between all possible combinations. For each member of our sample, we then selected the facility in the spatial inventory with the lowest Levenshtein distance (i.e., the nearest pair).

To maximize pair accuracy, we separately conducted matching among primary health facilities (i.e., FSPs and CSBs) and among hospitals (i.e., CHDs, CHRRs, and CHUs). For primary health facilities, the full, standardized facility names included the facility's region, district, and commune; for hospitals, the full name included the region and district only. To apply a conservative matching approach, we restricted matches to those with a Levenshtein distance no greater than 2.

Using this approach, 1,768 facilities (52%) in our sample were matched to validated coordinates, of which 1,685 facilities were matched based on identical string matches, 79 facilities were matched based on string matches with a Levenshtein distance of 1, and 25 facilities were matched based on string matches with a Levenshtein distance of 2.

Step 2: Matching to facility data from RHINoVision Decision Support System

We then gathered public health facility coordinate data from the RHINoVision Decision Support System,⁸⁰ which supports an open source database of health facility data in conjunction with USAID, the government of Madagascar, and other stakeholders.

RHINoVision's spatial inventory included coordinates for 3,171 primary health facilities in Madagascar.

We applied the same approximate string matching technique as in Step 1 against the RHINoVision spatial inventory, restricting matches only to primary health facilities in our sample (so as not to allow hospitals to be matched against the spatial inventory of basic health facilities).

Following visual inspection of the nearest approximate pairs, we retained matches with a maximum Levenshtein distance of 3, to allow for greater flexibility in matching.

Using this approach, 827 facilities were matched to coordinates in the RHINoVision spatial

inventory, of which 677 facilities were matched based on identical string matches, 64 facilities were matched based on string matches with a Levenshtein distance of 1, 54 facilities were matched based on string matches with a Levenshtein distance of 2, and 38 facilities were matched based on string matches with a Levenshtein distance of 3. (Six matches were duplicates and were removed.)

In total, matching to our expanded inventory in Step 2 led to 2,595 facilities (76% of our sample) being geolocated.

Step 3: Matching to any spatial sources

To geolocate the remaining facilities, we expanded our spatial inventories with health facility coordinates gathered from local consultants, the Global Healthsites Mapping Project, and other sources to create an expanded database of 13,534 uniquely identified coordinates.

We removed pharmacies from our spatial inventory, as pharmacies were not included in our sample. Removing pharmacies from our expanded spatial inventory resulted in 13,358 coordinates available for matching.

Most of the coordinates in this expanded inventory were duplicates, as the same facility would appear in different sources. Importantly, coordinates for the same facility could be slightly different across sources, due to variation in precision and geolocation.

Using the same approach to uniquely identifying facilities in our sample, we grouped coordinates in our expanded inventory by facility name, type, and geographic information (namely, which commune, district, and region a coordinate fell within). In other words, in order to be grouped together, coordinates would need to be of the same facility type and name, and would need to be located in the same region and in the boundaries of the same district (for hospitals) or commune (for all other facilities).

Grouping resulted in 6,112 coordinate groups in our expanded inventory. Of these, 1,764 consisted of three or more coordinates, 762 consisted of two coordinates, and 3,586 consisted of a single

coordinate.

In order to evaluate whether groups of two coordinates (which we referred to as “line groups”) and groups of three or more coordinate (“polygon groups”) were internally consistent (i.e., the points within a group were not geographically far apart, suggesting uncertainty in the location of a facility), we calculated the length (for line groups) and area (for polygon groups) of groups with more than one coordinate.

We applied an arbitrary restriction to line and polygon groups, such that the length or area, respectively, would not exceed a particular threshold. The threshold for length (15 km.) was selected to be approximately half the distance of one side of a spatial climate resolution tile (~30 km for ERA-5 data). The threshold for area (225 km^2) was assigned to be the length threshold, squared. Groups that exceeded their respective thresholds were discarded.

Among polygon groups, the mean area was 0.69 km^2 , with a maximum area of 91 km^2 . At the threshold of 225 km^2 , all polygon groups fell within the cut-off. Among line groups, the mean distance between coordinates was 1.95 km, with a maximum distance of 54 km. At the threshold of 15 km, 745 line groups fell within the cut-off (98% of line groups).

After applying the thresholds, we retained 6,095 coordinate groups in our expanded inventory.

To identify a single coordinate from each group, we computed the convex hull of polygon groups and selected the centroid of the grouped coordinates. For line groups, we selected the midpoint. For groups with a single member, the coordinates of that sole member were used.

We then applied the same approximate string matching technique as in Step 1, using the remaining facilities without geolocations in our sample and the expanded spatial inventory. To maximize match accuracy, we applied the approximate string matching technique separately based on the three geographic levels of service, akin to our approach in Step 1. In other words, regional facilities in our sample are only evaluated for possible matches against regional facilities in the

expanded spatial inventory, and so one for district-level facilities and for commune-level facilities.

Visual inspection of closest pairs across the regional, district, and commune level facilities indicated that likely matches had a Levenshtein distance no greater than 3.

Using this approach, 326 facilities were matched to coordinate groups in our expanded spatial inventory, including 22 regional facilities, 32 district-level facilities, and 272 commune-level facilities. In total, matching to our expanded inventory in Step 3 led to 2,921 facilities (86% of our sample) being geolocated.

Step 4: Manual matching to coordinates in the expanded spatial inventory

Despite the use of approximate string matching in Step 3 to link facilities in our sample to coordinates in our expanded spatial inventory, visual inspection and comparison of unmatched facilities to the spatial inventory revealed match failures due to variations in clinic names (e.g., “Notre Dame De Bon Remede Kiranomena” versus “Notre Dame de bon Remède”), clinic types (e.g., FSP and CSB facilities being coded interchangeably), district names (e.g., Toliary-I versus Toliary-II), and commune names (e.g., Toliara I versus Tanambao I).

We manually reviewed unmatched facilities and identified those with unambiguous matches to the spatial inventory which, for various reasons, failed to match under Step 3.

Manual matching allowed for an additional 122 facilities in our sample being linked to coordinates in our expanded spatial inventory. In total, matching to our expanded inventory in Step 4 led to 3,043 facilities (89% of our sample) being geolocated.

Step 5: Using commune and village centroids as proxies for facility locations

Among commune-level facilities, there are two potential catchment areas: communes and *fokontany* (villages). Many CSB facilities are named after the village they are located in; this provided us with additional information that could be helpful in geolocation.

While it would be ideal to obtain precise locations for each facility in our sample, for the purposes

of our analysis, an approximate location would be sufficient, given the spatial resolution of the climate data we used. The spatial resolution of ERA-5 and ESA-CCI data is approximately 30 km., meaning that all coordinates within a spatial tile of 900 km² will have the same time series for a given variable. Furthermore, neighboring tiles are unlikely to have extraordinarily different time series, underscoring that close approximate locations would likely result in minimal impact to the analysis versus exact coordinates.

For commune-level facilities, knowing the catchment area may therefore be just as informative as knowing the facility's precise location if the catchment area was sufficiently small. Determining a cut-off was, again, arbitrary; to adopt a conservative threshold, we considered a catchment area small if its area was no greater than 225 km², which corresponded to approximately 25% of the area of a climate data spatial resolution tile (Figure 24).

To exploit all available information for geolocation, we first used approximate string matching to link facilities named for their locations in our sample to known *fokontany*, based on the facility name and catchment area; if the village area was smaller than our threshold, the centroid of the village was used as a proxy for the facility location. We then applied the same approach to unmatched commune-level facilities to known communes.

Visual inspection of village and commune matches indicated that likely matches had a Levenshtein distance no greater than 1. Using approximate string matching, we linked 56 facilities to *fokontany* with identical string matches and 3 facilities with near identical matches. After applying our threshold, 55 facilities in our sample were matched to *fokontany* centroids. We were then able to link 225 facilities to communes with identical string matches and 6 facilities with near identical matches. After applying our threshold, 200 facilities in our sample were matched to commune centroids.

Altogether, matching to centroids of communes and *fokontany* in Step 5 led to 3,298 facilities (97% of our sample) being geolocated.

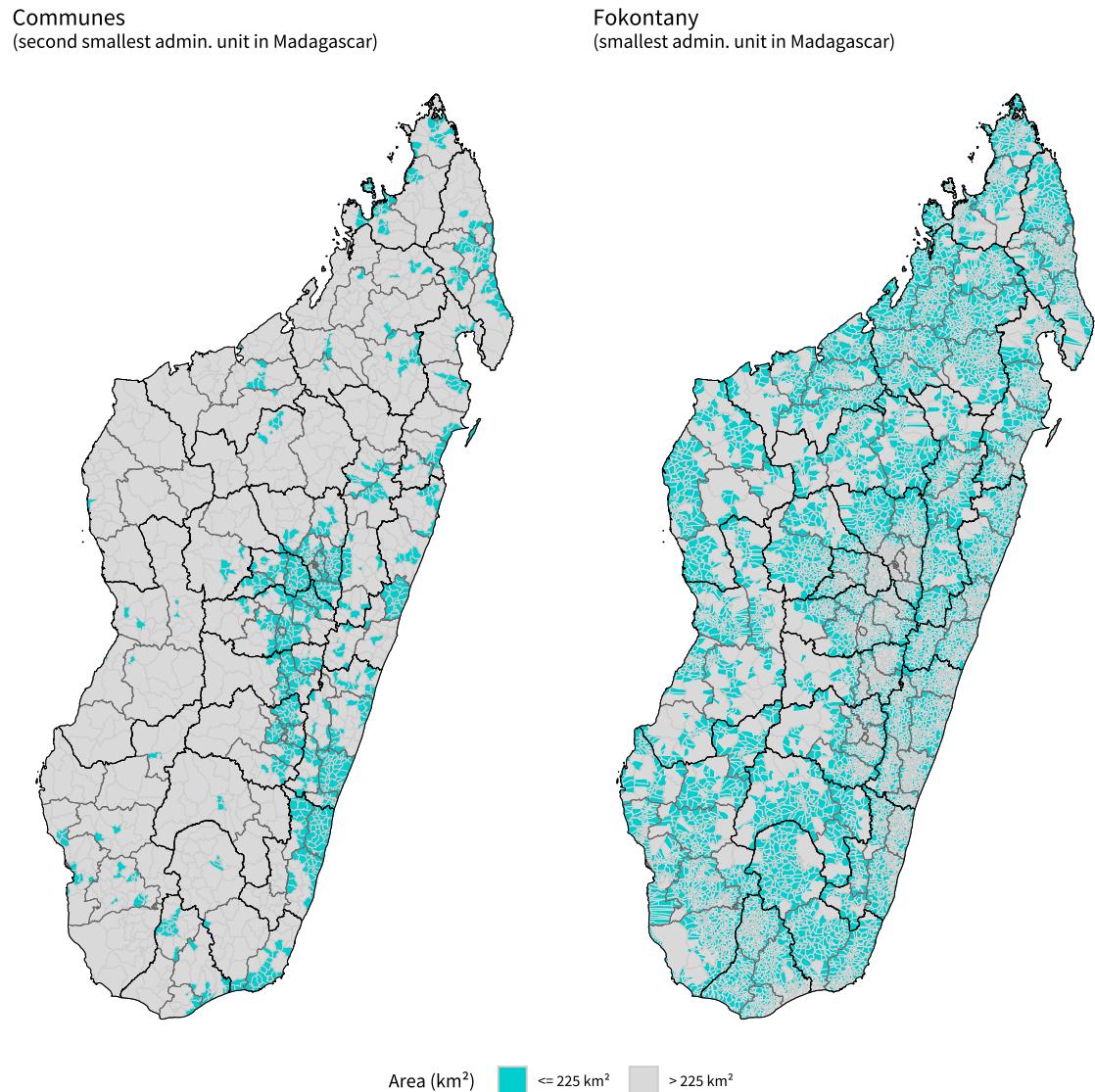


Figure 24: Communes and fokontany in Madagascar, by area. Units colored in teal are within the 225 km^2 threshold for use in Step 5 of the matching process.

Step 6: Targeted searches

We then conducted targeted searches to identify coordinates for unmatched facilities from Google Maps, Mapcarta, and other sources. We identified coordinates for 115 unmatched facilities.

Combined with the previous steps, targeted searches led to 3,413 facilities (100% of our sample) being geolocated.

Validation To verify the accuracy of the geolocating process, we randomly selected 1% of our sample of geolocated facilities ($n = 34$) and independently identified coordinates for each facility. We then compared these coordinates to those identified from our geolocating process. We then calculated the physical distance between the independently identified coordinates and the coordinates identified from our geolocating process for each facility. Table S2.10 provides the list of facilities in the validation sample.

Table S2.10: Sample of facilities for validation

Region	Clinic name	Longitude	Latitude
Alaotra Mangoro	MSI Ambatondrazaka	48.43	-17.83
Alaotra Mangoro	EKAR Andasibe	48.41	-18.92
Amoron I Mania	Ambohibolafotsy	47.45	-20.24
Amoron I Mania	Betsimiosotra	47.51	-20.28
Analamanga	CML Andoharanofotsy	47.53	-18.98
Analamanga	CML Finaritra Malaho	47.51	-18.97
Analamanga	Anjoma Faliarivo	47.75	-19.33
Analanjirofo	Anivorano	49.95	-16.8
Analanjirofo	Ambodivoanio	49.67	-16.18
Androy	Beraketa	45.68	-24.18
Androy	MONJA Jaona	46.08	-25.18
Androy	Antseta	45.13	-25.22
Atsimo Andrefana	Ankazomanga Ouest	44.13	-23.65
Atsimo Andrefana	Besely	44.44	-23.74
Atsimo Andrefana	BETESDA	43.68	-23.34
Boeny	Antsirabe	45.65	-16.83
Diana	Ambatoharana	49.04	-12.91
Diana	Marotolana	48.62	-14.02
Haute Matsiatra	Ambalakely	47.17	-21.42
Ihorombe	Ranomena	46.8	-22.7
Ihorombe	Anarabe	46.67	-23.1
Itasy	Mandriavato	47.02	-19.08
Menabe	SALFA Morondava	44.29	-20.3
Menabe	Belo Tsiribihina	44.54	-19.7
Sava	Antsahampano	49.73	-13.2
Sofia	Andranomeva	47.77	-15.8
Sofia	Ambodiadaboo	49.18	-14.65
Sofia	Ambodirafia	48.47	-14.53
Vakinankaratra	Antanimandry	46.96	-19.85
Vakinankaratra	Mandriankeniheny	47	-19.93
Vakinankaratra	Antsiravaza	46.87	-20.06
Vatovavy Fitovinany	Morarano Tody	47.93	-21.32
Vatovavy Fitovinany	Tataho	47.97	-22.14
Vatovavy Fitovinany	Antaretra	47.78	-21.36

Comparing the geolocated coordinates to validated coordinates for each facility, the mean distance between coordinates in the validation sample was 1.36 km., with a maximum distance of approximately 9.5 km. The distance between geolocated and validated coordinates for each of the facilities in the validation sample is reported in Table S2.11.

Table S2.11: Distance between geolocated and validated coordinates

Facility name	Distance (km)
CSB1 Ambatoharana	0
CSB1 Anarabe	0
CSB1 Anjoma Faliarivo	0
CSB1 Besely	0
CSB2 Antanimandry	0
CSB2 Betsimiosotra	0
FSP CML Finaritra Malaho	0
FSP EKAR Andasibe	0
CSB2 Tataho	0
CSB2 Antaretra	0
CSB2 Mandriankeniheny	0
FSP MSI Ambatondrazaka	0
CSB1 Ambohibolafotsy	0.1
FSP SALFA Morondava	0.1
CSB2 Ambalakely	0.2
CSB1 Antsirabe	0.5
CSB2 Ankazomanga Ouest	0.5
CHRR MONJA Jaona	0.5
CSB2 Andranomeva	0.6
CSB2 Belo Tsiribihina	0.7
CSB2 Ambodivoanio	0.8
CSB2 Marotolana	0.9
CSB2 Beraketa	1
CSB2 Mandiavato	1.2
CSB1 Antsahampano	1.4
CSB1 Ambodirafia	1.4
CSB1 Anivorano	1.5
FSP BETESDA	1.7
CSB2 Ambodiadabo	1.7
CSB1 Ranomena	2
CSB1 Morarano Tody	5.5
CSB1 Antsiravaza	7.2
CSB1 Antseta	7.2
FSP CML Andoharanofotsy	9.5

From this analysis, we drew strong confidence in the accuracy of our geolocating process and proceeded to obtain climate data for the identified coordinates in our sample.

Glossary

Translations:

- *Andrefana*: west (Malagasy)
- *Atsimo*: south (Malagasy)
- *Atsinanana*: east (Malagasy)
- *Avaratra*: north (Malagasy)
- *Est*: east (French)
- *Haute*: high (French)
- *Nord*: north (French)
- *Ouest*: west (French)
- *Sud*: south (French)
- *Vaovao*: new (Malagasy)

Acronyms:

- *CMC*: *Clinique Médico-Chirurgicale* (French), medical-surgical clinic
- *EKAR*: *Eglisy Katôlika Apôstôlika Rômanina* (Malagasy), the Roman Catholic Church
- *FJKM*: *Fiangonan'i Jesoa Kristy eto Madagasikara* (Malagasy), the Church of Jesus Christ in Madagascar
- *MSI*: MSI Reproductive Choices, formerly Marie Stopes International
- *SALFA*: *Sampanasa Loterana momba ny Fahasalamana* (Malagasy), the health care program of the Malagasy Lutheran Church