A Breathtaking Gap in the Social Cost of Carbon

Valuing Health Losses from Climate Change

Lawrence Hsu

University of Toronto

May 19, 2026

UNIVERSITY OF TORONTO

Disclaimer and Land Acknowledgement

- **Disclaimer**:

  The models and frameworks presented here reflect the personal opinions of the author and do not represent the official views or positions of the Department of Economics or the University of Toronto. All errors remain my own.

- **Land Acknowledgement**:

  I wish to acknowledge this land on which the University of Toronto operates. For thousands of years, it has been the traditional land of the Huron-Wendat, the Mississaugas, and the Seneca of the Credit. Today, this meeting place is still the home to many Indigenous people from across Turtle Island, and we are grateful to have the opportunity to work on this land.

Outline: Price Carbon, Trace Health, Value Morbidity

1. **Motivation**:
   Incumbent social cost of carbon models price mortality much better than morbidity
2. **Climate Panel**:
   DICE maps marginal CO_2 pulses into temperature and extreme weather
3. **Health Panel**:
   GBD data in YLD, incidence, and treatment coverage create latent morbidity
4. **Distributional Valuation**:
   GRACE-CRRA turns distributional health loss into undiscriminative monetary values
5. **Main Conclusion**:
   Closing the morbidity gap could increase the value of social cost of carbon up by 15%

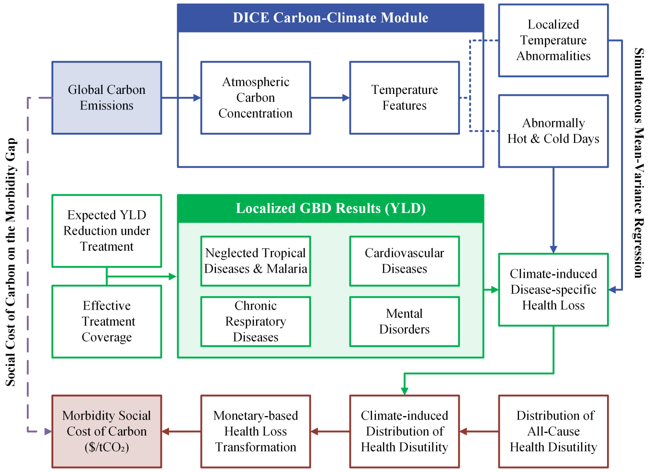
The Social Cost of Carbon Aims to Prices Marginal Emissions of CO_2, but Incumbent Damage Modules Still Miss Morbidity Measurements

- **What is the Social Cost of Carbon (SCC)?**
  - It is the present-value damage from emitting *one extra metric ton* of CO_2
  - It converts climate damages into *a dollar* benchmark for policy
  - In practice, it is the shadow price behind justified carbon pricing
- **Why Morbidity Matters in the Current Literature?**
  - Most health-SCC work focuses on premature death without discussing years lived with disease
  - YLD-based valuation adds the missing “living with disability” channel—the **Morbidity Gap**

Existing SCC Modules and Tools are Constantly Improving, But Morbidity is Still Largely Uncaptured Upon Current Scopes

- **The Four SCC Modules**
  - Socioeconomic Module
  - Climate Module
  - Discounting Module
  - Damage Module [Structurally refined in a recent paper by Burke *et al.* (2026)]
- **The Literature Gap I Target from Other IAM Results**
  - Bressler (2021) extends DICE with temperature-related mortality
  - Rennert *et al.* (2022) update SC-CO_2 with GIVE and report \$185/tCO_2 at $r = 2\%$
  - Cromar *et al.* (2022) recommend broader health endpoints and better climate parameters
  - My Extension: non-fatal morbidity through YLD and GRACE valuation
    The Research Question is Simple: *"What is the Morbidity SCC?"*

I Connect Carbon Emissions to Disability-Adjusted Monetary Valuations Through a Modular Climate–Health Pipeline



UNIVERSITY OF TORONTO

I Use Publicly Available Climate Data and Global Burden of Diseases Health Outcome Measures to Calibrate the Pipeline

- **Climate Panel**
  - Our World in Data: Global Carbon Data, 1750-2024
  - NOAA: Atmospheric CO_2 Concentration, 1959-2024
  - NASA POWER: Daily Temperature, 1988-2020
  - Niño 3.4: ENSO Sea-Surface-Temperature Index, 1950-2024
- **Health Panel**
  - Data Source: Global Burden of Disease, 1990-2019
  - Top 60 countries with primate-city weather proxies plus 7 large countries by subgroups
  - Disease groups: vector-borne, cardiovascular, chronic respiratory, and mental disorders
  - Variables: population, YLD, incidence, treatment coverage, and all-cause YLD distribution

I Use Nordhaus's DICE-2016R-Style Climate Bridge to Isolate the Morbidity Contribution

- **Carbon-to-Temperature Bridge**
  - Combined DICE-2016R-style carbon-cycle and two-layer temperature module DICE Formula
  - A one-GtC pulse creates the marginal temperature path used for SCC damages Pulse Function
  - *"Why not the 'up-to-date' DICE-2023 or DFAIR models?"*
    To *isolate the health effects* before adding updated risk and carbon-sink saturation
- **Valuation Anchor**
  - Direct DALY Benchmark: \$100,000 per DALY-year
  - GRACE Benchmark: distributional HRQoL values normalized to \$100,000 at perfect health
  - Climate economists use VSL as their common benchmark (2.0-7.5 $\times$ of the \$100K threshold)
  - Rennert *et al.* (2022) with DICE-2016R: All-cause non-injury excess mortality at \$90/tCO_2
    Question: *"If mortality SCC is already large, how much larger is SCC after morbidity?"*

UNIVERSITY OF TORONTO

Extreme Days and Mean–Variance-Controlled Models Capture the Climate Signal Closer to How People Actually Feel

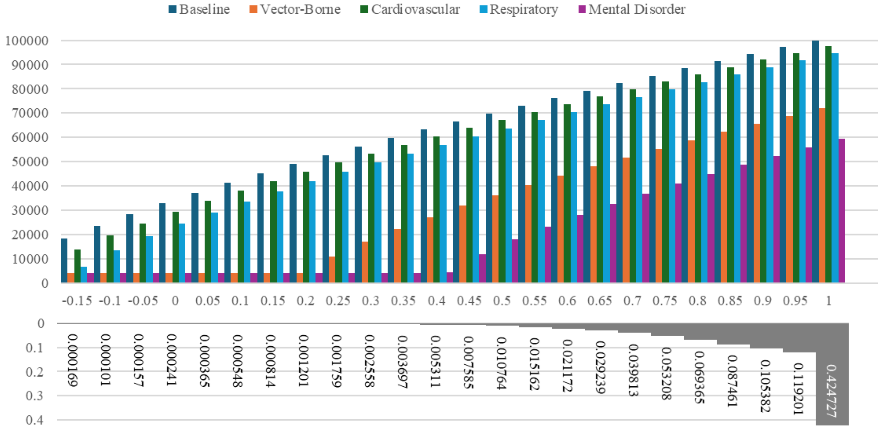
- **Abnormal Cold and Hot Days**
  - For climate economists, extremity controls are considered empirical observations
  - Definition: below 5^{th} percentile of T_{min} vs. above 95^{th} percentile of T_{max}
  - Forecast future tails through local moment shifts Moment Methods
- **Simultaneous Mean–Variance Regression (SMV)**
  - Developed by Spady & Stouli (2019) to assign variance penalties under parametric assumptions
  - The linear regression replacement controlling both drifts (mean) and diffusions (deviations)
  - SMV treats traditional error terms as a climate features based on its aggregated nature SMV Formula
- Variability Premium: difference between direct TWFE results and SMV with extreme controls

  Results: YLD is **6.7% higher** through mean temperature (Latent YLD is at least 8.0% higher)

Treatment Counterfactuals Recover Latent YLD that Climate can Push Further Upward

- **Health Gains from Treatments**
  - I match 1990 and 2020 treatment frontiers (with polynomial smoothing) using RWE-informed remission, stabilization, and functional-improvement gains Literature
  - Top 5 diseases dominate each group ⇒ Incidence-weighted gain approximates group-level frontiers
  - This is not a cure assumption: chronic conditions are stabilized, not erased Frontier Estimations
- **Effective Treatment Coverage**
  - GBD Effective Coverage proxies the share receiving care at *sufficient quality* Coverage Estimation
  - Counterfactual YLD without treatment plus observed YLD gives **Latent YLD**

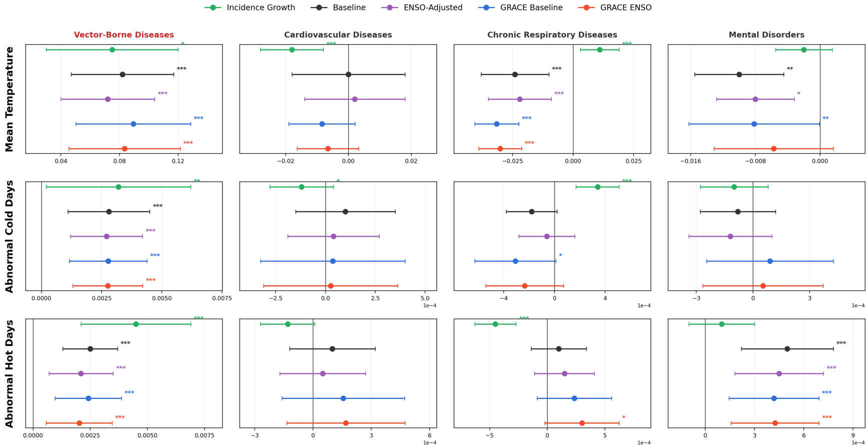
The Generalized Risk-Adjusted Cost-Effectiveness (GRACE) Model Turns the Same HRQoL Loss into a Severity-Sensitive Monetary Value



A Population-Specific Distributional Health State Gives Macro-Level Estimate Solid Micro-Foundations

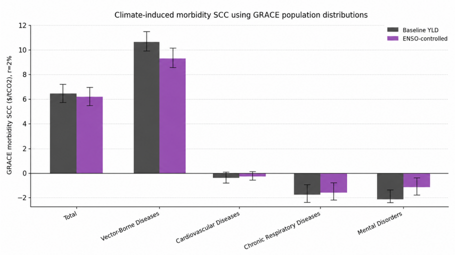
- **Initial health-state distribution**
  - I initialize a left-skewed HRQoL distribution with $\alpha = -2$ and $\sigma \approx 0.20$
  - Age group and sex population shares turn each country/subcountry into a weighted YLD mixture
  - Incidence applies the disease shock to the people entering that health state Binning Formula
- **GRACE application**
  - Basu and Lakdawalla (2025) make GRACE usable by mapping EQ-5D/HRQoL to VAS health
  - YLD is interpreted as HRQoL loss due to health-state decrements over time
    (a 30% heterogeneous gap is acknowledged, but irrelevant to later transitions in SCC)
  - I monetize 24 HRQoL blocks from -0.15 to 1.00, censoring at both bounds Interpolation Formula

Vector-Borne Diseases are Consistently Climate-Responsive While Other Groups Move Through Mixed Extremes



UNIVERSITY OF TORONTO

Monetary Valuation of Morbidity SCC Remains Positive After Controls Even After "Cold-Benefits" Aggregated with Smoothed Extreme Days



- Vector-borne YLD is the main positive signal; cardiovascular, respiratory, and mental results partly *offset* through cold and trend channels

- Given the discounted damage from 2020-2100 **Baseline GRACE SCC ≈ $6.5/t$CO_2$** **ENSO-adjusted GRACE SCC ≈ $6.2/t$CO_2$**
- The perpetual ($T \to \infty$) damage ≈ **$7.8/t$CO_2$**
- Matching Rennert *et al.* (2022) via fixed VSL: Morbidity SCC ≈ $32.8–$34.4/tCO_2; which stands for **17.8%–18.6%** of incumbent SCC
- The result is conservative—annual GBD panels smoothes acute mental and respiratory shocks

UNIVERSITY OF TORONTO

Three Results Explain Why Morbidity Belongs Inside the SCC

- **Result 1: Vector-Borne Morbidity is a Clean Climate Channel**
  - Mean temperature, abnormal cold, and abnormal hot days are positive across specifications
- **Result 2: Extremes Matter Even When Annual Means are Noisy**
  - Cold and hot tails explain signs that annual mean temperature alone would misread
- **Result 3: Distributional Valuation Changes the Damage Interpretation**
  - GRACE prices health loss more heavily when it hits already-sicker health states
  - The total GRACE morbidity SCC remains positive even after mixed disease-group offsets

The Main Caveats Likely Bias the Morbidity SCC Downward

- **Noisy Health Trends**
  - Representative cities are imperfect proxies for national exposure
  - Annual GBD data smooth acute mental and respiratory responses
  - Extreme-weather prediction remains sensitive to pattern scaling
  - Potential Remedy: dynamic structural models with after-shock calibration
- **Data Granularity and GBD Limits**
  - Initial HRQoL distribution is generated, not observed directly
  - Treatment effects are simplified as remission/stabilization frontiers
  - Disability–mortality tradeoffs need richer microdata
  - Potential Remedy: synthetic controls with policy and population adjustments

Economic Evaluation Tools Bridge the Health-SCC Link and Close the Morbidity Gap of By Incorporating Incumbent IAMs

- **Climate Econometrics Expands the Societal Perspective**
  - GBD YLD adds the missing non-fatal health component
  - Distributional HRQoL makes valuation less blind to severity
- **The Conservative Estimate is Still Policy-Relevant**
  - Vector-borne morbidity is well indicated with current data
  - Extreme-weather preparedness is justified even before a full morbidity model is complete
  - The GRACE morbidity module captures about \$6-7/tCO_2 in additional health damages
  - VSLY-matched sensitivity implies a larger policy-relevant gap
- **Takeaway**
  - By closing the morbidity gap, incumbent social cost of carbon rises by *at least 15%*

Thank You for Your Attention :)

Lawrence Hsu (University of Toronto)
lawrence.hsu@mail.utoronto.ca

UNIVERSITY OF TORONTO

Appendix: Formulas and Literature Logic Behind the Modelling Flow

- DICE Carbon Cycle
- Temperature and Pulse
- Extreme-Day Emulator
- SMV Regression

- Treatment Counterfactuals
- Health-State Distribution
- GRACE Valuation
- Morbidity SCC

DICE Carbon Cycle: How Emissions Become Atmospheric CO_2

$$\underbrace{M_{t+1}^{AT}}_{\text{Carbon Mass: Atmosphere}} = \underbrace{E_t}_{\text{Annual Emissions}} + \phi_{11} M_t^{AT} + \phi_{21} M_t^{UP}$$

$$\underbrace{M_{t+1}^{UP}}_{\text{Carbon Mass: Upper Ocean}} = \phi_{12} M_t^{AT} + \phi_{22} M_t^{UP} + \phi_{32} M_t^{LO}$$

$$\underbrace{M_{t+1}^{LO}}_{\text{Carbon Mass: Lower Ocean}} = \phi_{23} M_t^{UP} + \phi_{33} M_t^{LO}$$

$$\underbrace{F_t}_{\text{Radiative Forcing}} = \underbrace{\eta}_{\text{Forcing from Doubling } CO_2} \log_2 \Big(\underbrace{C_t}_{\frac{M_t^{AT}}{2.13}} \Big/ \underbrace{C_{1750}}_{C_t \text{ without Emissions}} \Big) + \underbrace{F_t^{EX}}_{\text{Exogenous Forcing}}$$

Back to DICE Slide

Two-Layer Temperature Model: Concentration Becomes Warming

$$\underbrace{T_{t+1}^{AT}}_{\text{Atmospheric Temperature}} = T_t^{AT} + \xi_1 \left[F_t - \overbrace{\left(\frac{\eta \cdot T_t^{AT}}{\underbrace{ECS}_{\text{Equilibrium Climate Sensitivity}}} \right)}^{\text{Climate Feedback}} - \underbrace{\xi_2 (T_t^{AT} - T_t^{LO})}_{\text{Ocean Heat Exchange}} \right]$$

$$\underbrace{T_{t+1}^{LO}}_{\text{Lower Ocean Temperature}} = T_t^{LO} + \xi_3 (T_t^{AT} - T_t^{LO})$$

$$\underbrace{\mathcal{D}T_t^{AT}}_{\text{Temperature Impulse}} = T_t^{AT,pulse} - T_t^{AT,base}; \qquad SCC_t = \sum_{\tau=t}^{T} \frac{\text{Damages}(\mathcal{D}T_\tau^{AT})}{(1+r)^{\tau-t}}$$

Back to DICE Slide

Extreme-Day Emulator: The Shifting Local Tails

$$\underbrace{\mu_i(t)}_{\text{Local Mean Temperature}} = \mu_i(2019) + \beta_i^{\mu}\left[T_t^{AT} - T_{2019}^{AT}\right]$$

$$\underbrace{\sigma_i(t)}_{\text{Local Temperature Dispersion}} = \sigma_i(2019) + \beta_i^{\sigma}\,[T_t^{AT} - T_{2019}^{AT}]$$

$$\underbrace{Cold_i(t)}_{\text{Abnormal Cold Days}} = 365 \cdot \Phi\left(\frac{c_i - \mu_i^{min}(t)}{\sigma_i^{min}(t)}\right)$$

$$\underbrace{Hot_i(t)}_{\text{Abnormal Hot Days}} = 365 \cdot \left[1 - \Phi\left(\frac{h_i - \mu_i^{max}(t)}{\sigma_i^{max}(t)}\right)\right]$$

Back to Climate-Feature Slide

SMV Regression: Dispersion is a Climate Outcome, Not Nuisance Noise

$$\underbrace{Y_{it}}_{\text{Climate Feature}} = X_{it}'\beta + \underbrace{s(X_{it}'\gamma)}_{\text{Conditional Scale}} \varepsilon_{it}$$

$$(\hat{\beta}, \hat{\gamma}) = \arg\min_{\beta,\gamma} \sum_{i,t} \frac{1}{2} \left[\underbrace{\frac{(Y_{it} - X_{it}'\beta)^2}{s(X_{it}'\gamma)}}_{\text{Weighted Prediction Error}} + \underbrace{s(X_{it}'\gamma)}_{\text{Variance Penalty}} \right]$$

$$\Delta \ln T_{it} = \theta_\mu \Delta\mu_{it} + \theta_\sigma \Delta\sigma_{it} + \theta_C \Delta Cold_{it} + \theta_H \Delta Hot_{it}$$

Back to Climate-feature Slide

UNIVERSITY OF TORONTO

Treatment Counterfactual: Realized Care Added to Latent Burden

$$\underbrace{G_{g,t}}_{\text{Expected Health Gain}} = \sum_{d\in g} \underbrace{w_{d,t}}_{\text{Incidence Weight}} \times \underbrace{q_{d,t}}_{\text{YLD Loss from Stabilization}}$$

$$\underbrace{(\text{Averted})\ YLD_{i,g,t}}_{\text{Treated Counterfactual}} = \underbrace{ETC_{i,t}}_{\text{Effective Treatment Coverage}} \times G_{g,t} \times \underbrace{Incidence_{i,g,t}}_{\text{New Cases}}$$

$$\underbrace{(\text{Latent})\ YLD_{i,g,t}}_{\text{Burden without Treatment}} = \underbrace{(\text{Observed})\ YLD_{i,g,t}}_{\text{GBD Observed}} + \underbrace{(\text{Averted})\ YLD_{i,g,t}}_{\text{Treatment Removed}}$$

Back to Treatment Slide

Effective Treatment Coverage: From Access to Quality-Adjusted Care

$$\underbrace{ETC_{i,t}}_{\text{Effective Coverage}} = \underbrace{Coverage_{i,t}}_{\text{Received Care}} \times \underbrace{Quality_{i,t}}_{\text{Effective Care}}$$

$$\underbrace{L_{i,g,t}}_{\text{Latent YLD per Capita}} = \frac{\text{(Latent) } YLD_{i,g,t}}{\text{Population}_{i,t}}$$

$$\underbrace{x_g}_{\text{HRQoL Decrement per Incident Case}} = \frac{\sum_i \text{Population} \times L_{i,g,2019}}{\sum_i \text{Population}_{i,2019} \times \%Incidence_{i,g,2019} \times Persistence_{i,g,2019}}$$

Back to Treatment Slide

UNIVERSITY OF TORONTO

Distributional Health: 24 Blocks Turn Population into State-Mass

$$\underbrace{H_j}_{\text{HRQoL Blocks}} \in \{ \overbrace{-0.15}^{\text{Nonnegative Constraint}}, -0.10, \ldots, 0.95, \overbrace{1.00}^{\text{Perfect Health}} \}$$

$$\underbrace{\pi_{i,j}}_{\text{Population Share}} = \sum_{a,s} \underbrace{\omega_{i,a,s}}_{\text{Age–Sex Population Share}} \cdot \underbrace{\mathbb{P}[H_j \mid \alpha = -2, \sigma_i]}_{\text{Left-Skewed Initial Health}}$$

$$\underbrace{H'_{j,g}}_{\text{Post-Disease Health}} = \max\{-0.15,\ H_j - x_g\}$$

$$\underbrace{\text{Population}_{i,j}}_{\text{Block Population}} = \text{Population}_i \cdot \pi_{i,j}$$

Back to Distribution Slide

UNIVERSITY OF TORONTO

GRACE-CRRA: Health Distribution Changes → Monetary Loss

$$\underbrace{H^{VAS}}_{\text{Mapped VAS Health}} = \max\{0.19 + 0.70\underbrace{H}_{\text{HRQoL}}, \underbrace{0.01}_{\text{Nonnegative Constraint}}\}$$

$$\underbrace{W(H)}_{\text{GRACE utility}} = \frac{(H^{VAS})^{1-\eta}}{1-\underbrace{\eta}_{=0.28}}$$

$$\underbrace{V(H_j)}_{\text{Dollar Value}} = \$100{,}000 \times \frac{W(H_j)}{W(1)}$$

$$\underbrace{Loss_{i,g}}_{\text{Incident Value Loss}} = \sum_j \text{Population}_{i,j} \times \%Incident_{i,g} \times \left[V(H_j) - V(H'_{j,g})\right]$$

Back to Distribution Slide

Morbidity SCC: Carbon Pulse Becomes Discounted GRACE Loss

$$\underbrace{\Delta YLD_{i,g,t}}_{\text{Climate-Induced Morbidity}} = \text{Population}_{i,t} \cdot L_{i,g,2019} \cdot \Delta \log L_{i,g,t}$$

$$\underbrace{Cost_t}_{\text{Annual GRACE Morbidity Cost}} = \sum_{i,g} \underbrace{\omega_{i,g}^{GRACE}}_{\text{Dollars per Latent YLD}} \cdot \Delta YLD_{i,g,t}$$

$$\underbrace{\text{Morbidity } SCC(\mathbb{T})}_{\text{Value as \$tCO}_2} = \frac{1}{\underbrace{3.664 \times 10^9}_{\text{Gigatonne Transformation}}} \sum_{t=2020}^{\overbrace{\mathbb{T}}^{\text{Terminal Year}}} \frac{\mathcal{D}Cost_t}{(1+r)^{t-2020}}$$

Back to Valuation Slide

UNIVERSITY OF TORONTO

Literature Supports Adding Morbidity Without Overclaiming Cure

- **Climate-economic modules**: Auffhammer *et al.* (2013) warn that weather aggregation can distort climate-econometric estimates
- **Health-SCC modules**: Cromar *et al.* (2022) recommend broader health endpoints and more climate parameters for SC-GHG (greenhouse gases) models
- **Mortality benchmarks**: Bressler (2021), Carleton *et al.* (2022), and Rennert *et al.* (2022) show that mortality alone can materially raise SCC estimates
- **Mean–Variance Regression**: Spady and Stouli (2019) motivate modelling conditional mean and variance jointly under heteroskedasticity assumptions
- **GRACE Valuation**: Following Lakdawalla and Phelps (2024) and the experiment by Mulligan *et al.* (2024), Basu and Lakdawalla (2025) provide a practical map from QoL weights to GRACE utilities

Note: DICE-2023 and DFAIR are Natural Robustness Checks

- DICE-2023 updates carbon and climate modules:
  non-industrial GHGs, risk treatment, discount rates, and damages
- DFAIR makes the carbon cycle less like a constant sponge: sinks saturate as cumulative emissions rise
- I keep DICE-2016R-style equations in the baseline to isolate the new morbidity/GRACE damage module
- Next version: rerun the same health module under DICE-2023/DFAIR as an external sensitivity

Treatment Gains $\equiv$ Remission or Stabilization, Not Perfect Recovery

- **Mental Disorders**:
  remission, symptom response, relapse prevention, and functional recovery; do not assume cure
- **Respiratory Diseases**:
  fewer exacerbations, slower FEV1 decline, and less hospitalization; structural lung damage remains
- **Cardiovascular Diseases**:
  fewer events, fewer hospitalizations, and better functional class; underlying risk remains
- **Implication**:
  treatment counterfactuals are conservative stabilization gains by reducing YLD, not for HRQoL $\rightarrow 1$

Back to Treatment Slide

Full Literature Used in the HRQoL Gain Measurement (1/2)

- **Vector-Borne Diseases** (Mordecai *et al.*, 2019):
  Malaria (Boni, 2022; Novartis*, 2025),
  Lymphatic Filariasis (Stone *et al.*, 2016; Kaviya *et al.*, 2026),
  Onchocerciasis (Hong *et al.*, 2019; Njeshi *et al.*, 2026),
  Chagas Disease (Trowell *et al.*, 2025; Olivera, 2026),
  Visceral Leishmaniasis (Meheus, 2010; Dhamnetiya *et al.*, 2025)

- **Cardiovascular Diseases** (Fan *et al.*, 2023):
  Ischemic Heart Disease (Cleland *et al.*, 1996; Cohen *et al.*, 2004),
  Stroke (Rothwell *et al.*, 2004; Saver *et al.*, 2015),
  Atrial Fibrillation and Flutter (Go *et al.*, 2003; Eckman *et al.*, 2018),
  Rheumatic Heart Disease (Mayosi *et al.*, 2009; Beaton *et al.*, 2017),
  Hypertensive Heart Disease (Kannel *et al.*, 1996; Vaduganathan *et al.*, 2020)

Back to Treatment Slide

Full Literature Used in the HRQoL Gain Measurement (2/2)

- **Chronic Respiratory Diseases** (Weidmann, 2025):
  Asthma (Sears *et al.*, 1990; O'Byrne *et al.*, 2018),
  Chronic Obstructive Pulmonary Disease (Calverley *et al.*, 2007; Lipson *et al.*, 2018),
  Pneumoconiosis (Steenland *et al.*, 1997; Hoy *et al.*, 2020),
  Interstitial Lung Disease / Pulmonary Fibrosis (Douglas *et al.*, 2000; Richeldi *et al.*, 2014),
  Bronchiectasis (Cole *et al.*, 1986; Chalmers *et al.*, 2019)
- **Mental Disorders** (Obradovich *et al.*, 2018):
  Anxiety Disorders (Cao *et al.*, 2024; Andrews *et al.*, 2018),
  Depressive Disorders (Jia *et al.*, 2011; Einarson *et al.*, 1999),
  Substance Use Disorders (Zhang *et al.*, 2024; Schackman *et al.*, 2016),
  Bipolar Disorder (Chen *et al.*, 2024; Keck *et al.*, 2003),
  Schizophrenia (Lai *et al.*, 2025; Marcus *et al.*, 2015)

Back to Treatment Slide