# Aligning science, rulemaking, and practice to strengthen carbon crediting

Carlos F. Gould[1]

[1]University of California San Diego.

Correspondence: cagould@health.ucsd.edu

**Abstract** Results-based climate finance mobilizes private capital for climate mitigation by paying for verified outcomes[1]. Multiple independent evaluations have shown that credited reductions routinely overstate actual ones—by 3x–14x across sectors[2–8]—but understanding of why or what to do about it is highly variable. To guide effective policy response, we develop a framework that decomposes the gap into three sources of error: implementation (what projects do and report), rulemaking (the methodologies that shape what is allowed), and the state of the science (what we know about the world). Focusing on cookstoves, where a sectorwide analysis estimated a ninefold gap[9], we show that most of the discrepancy reflects not what projects did but what approved rules permitted and what the science embedded in those rules has since overturned. Correcting biased benchmarks and outdated science, we estimate credits exceeded actual reductions roughly fivefold. Under reformed protocols, credits would be roughly 80% smaller but overstate reductions by only 1.6-fold. Every credit that does not correspond to a real reduction is an unaccounted emission warming the planet, purchased by someone who believed otherwise. For cookstoves, the stakes extend beyond carbon: household air pollution kills 3.1 million people per year[10], and carbon finance is one of the few mechanisms reaching them.

# Introduction

Results-based climate finance channels billions of dollars per year through a simple accounting fact: one credit equals one tonne of $CO_2$e reduced[1;11;12]. Recent evaluations suggest the accounting fails by large multiples—ninefold for cookstoves[9], seven- to fourteenfold for avoided deforestation[4;13], threefold or more for renewables[3;14]. These findings have destabilized voluntary carbon markets and prompted calls to abandon crediting in some sectors entirely[2;6–8], but they do not on their own explain why credits overshoot. The crediting gap can originate in project-level implementation, in the methodology rules that constrain or permit certain parameter choices, or in the physical science parameters embedded in the crediting equations[2;15]. Each source requires a different response.

Here we introduce a framework in which the gap between project-estimated carbon credits and the best estimate of actual reductions is separated into three categories: (Fig. 1): implementation (what projects do and how they measure it), rulemaking (what approved methodologies permit), and state of the science (physical parameters like the fraction of non-renewable biomass that evolve with evidence). Each maps to a distinct policy lever: operational oversight, regulatory revision, and scheduled scientific updates.

Our focus is on cookstoves. A third of the world's population still burn solid fuels for their daily energy needs, and the resulting household air pollution kills roughly 3.1 million per year[10]. Carbon credits are one of the few mechanisms directing private capital toward cleaner alternatives where public finance does not reach[16;17]. Gill-Wiehl, Kammen, and Haya (2024; hereafter GKH) found that credits from 51 such projects overstated actual reductions by 9.24×[9]. Credit prices dropped, the Integrity Council for the Voluntary Carbon Market (ICVCM) flagged most cookstove methodologies[18], and a sector that serves some of the world's poorest households faced an existential credibility problem.

To quantify the origins of the gap between credited and observed emissions reductions, we meta-analyze a new evidence base of more than 150 field studies to establish robust benchmarks for household behavior. This re-evaluation of the assumptions underlying previous overcrediting claims provides a forensic accounting of past performance and shows that most of the ninefold gap reflects not what projects did but what the rules permitted and what the science embedded in those rules has since overturned. In a forward-looking analysis that applies reformed methodologies and current scientific estimates to our historical sample, we find that these same projects would issue roughly one-fifth as many credits and limit residual overstatement to less than twofold. The stakes of getting this right are large: credits that do not correspond to real reductions represent warming that remains unaccounted for. Our decomposition shows that historical misestimation is traceable to methodological lenience and that reforms now under way address these principal sources, offering a path to keep private capital flowing to the people and places that need it most while ensuring it delivers the climate and health gains it claims.

## Independent verification in carbon offsets: the cookstove challenge

Accredited third-party auditors certify that projects comply with approved methods. Yet even when every rule is followed, projects can over- or under-credit relative to reality when approved defaults, measurement protocols, or sampling designs misestimate baselines, usage, or decay (Fig. 1). For cookstoves specifically, recent evidence suggests additionality and leakage are modest in rural settings[19], making quantification accuracy the dominant integrity concern[20].

Independent evaluations use outside data and explicit counterfactuals to test whether credited reductions actually occurred[2;21]. Satellite imagery for forests[4;13], grid dispatch data for renewables[3], and plant logs for industrial gases[22] now provide such tests across most major credit categories. The results are sobering: in REDD+, synthetic-control analyses estimate that only 7–13% of issued credits correspond to additional avoided deforestation[4;13]; in the CDM's largest categories, roughly 73% of credits may lack additionality[14]; and industrial-gas crediting created perverse incentives to overproduce waste gases[22;23]. In their recent review, Romm et al.[6] conclude that most project types are structurally unsuited to crediting due to the inherent subjectivity and information asymmetry involved in baseline setting but identify clean cooking as a rare exception where the problems are not intractable.

Table 1 maps these dimensions across the major credit categories. For forests and renewables, one dimension tends to dominate: baseline inflation for REDD+, additionality for grid-connected renewables. Cookstove overcrediting draws heavily from all three—behavioral measurement, permissive defaults, and outdated science parameters—which is what makes the decomposition informative.

Clean cooking projects are particularly challenging to evaluate relative to other sectors because they lack a ground truth. Household stove use cannot be observed from satellites, plant logs, or grid meters, so credits cannot be cross-checked with the same external records available

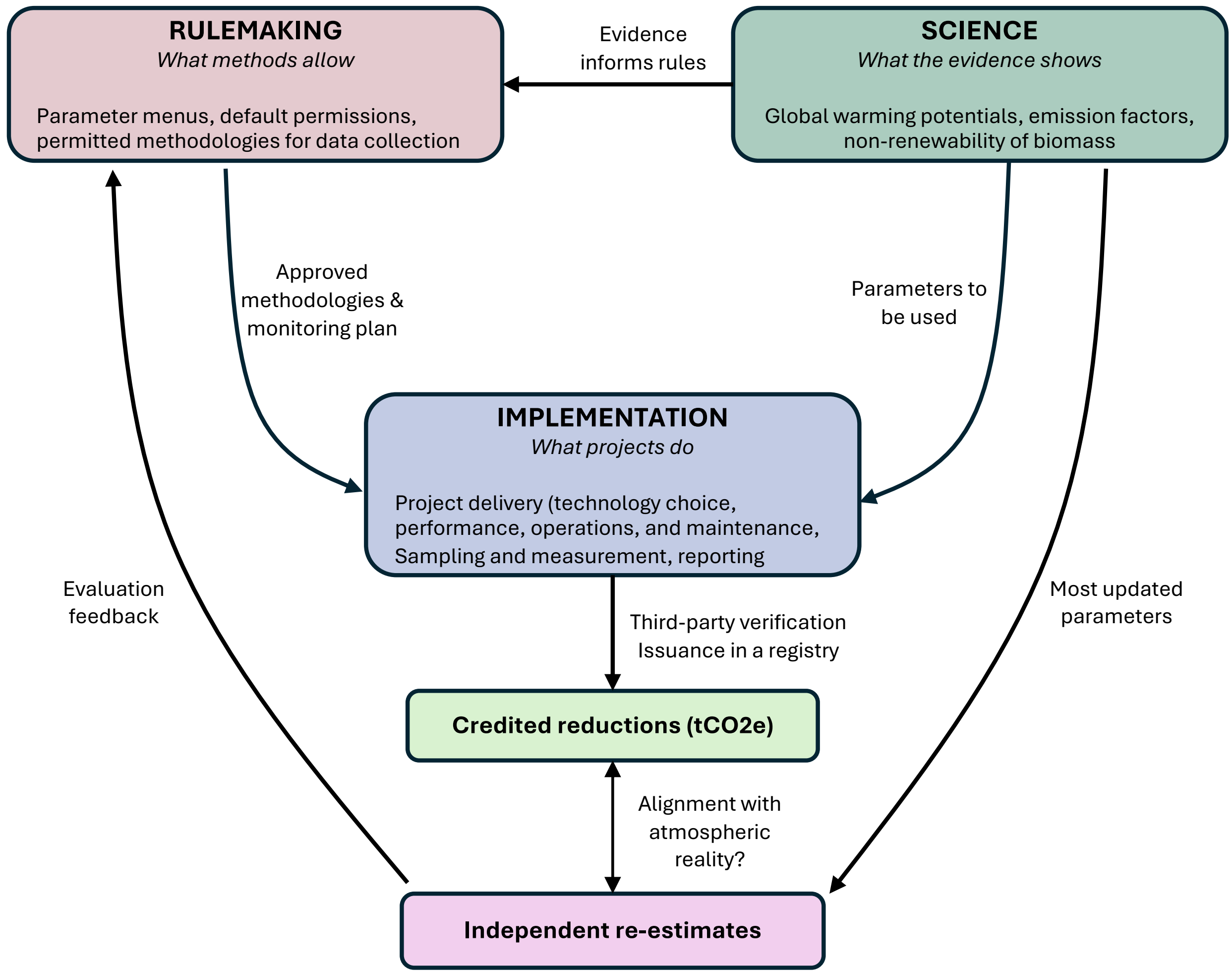


**Figure 1: Carbon crediting as a sector-level system combining rulemaking, science, and implementation.** An approved methodology and monitoring plan produces credited reductions (centre). Three upstream inputs shape credits: *Rulemaking* determines permissible parameters and whether measurement or defaults are required. *Science* provides physical parameters (emission factors, fNRB, charcoal yields, GWPs) that evolve with evidence. *Implementation* reflects what projects do: technology delivery, sampling, measurement, and data quality. Independent re-estimates (bottom) feed back to all three pillars.

elsewhere. Independent evaluations of carbon-financed cookstove projects are rare (three peer-reviewed studies)[24–26]. In their absence, buyers and reviewers rely on the broader academic literature to set expectations for adoption, use, and fuel savings. Those studies are informative but not interchangeable with project monitoring, because the two optimize for different things. Projects optimize for delivery: they target households likely to adopt, invest in follow-up and repairs, and manage for performance. Academic studies optimize for inference: they prioritize clean identification, limit researcher influence, and sample to isolate specific behaviors. Using research benchmarks to evaluate delivery programs—or vice versa—produces systematically misleading comparisons.

## How cookstove projects generate carbon credits

Cookistove projects replace inefficient stoves with cleaner technologies, primarily in sub-Saharan Africa, South Asia, and Latin America. But intermittent intervention stove use blunts the anticipated health, environmental, and climate gains[30–32], and affordability, fuel access, device quality, and user preferences all shape whether use is sustained[16;33;34].

Crediting converts observed changes in cooking practices to avoided $CO_2$e through two classes of parameters. Implementation parameters reflect project decisions: which households are targeted, the technology delivered, and how use is tracked. Projects also choose how to monitor outcomes: whom to sample and when, whether stove use is tracked using surveys or sensors, and how fuel consumption is measured. Within compliant protocols, choices about sampling, attrition handling, and analysis can move credited outcomes. Together, these elements quantify per-household fuel savings and the intensity and duration of use (stove-days) that drive credits.

State-of-science parameters then convert fuel savings into $CO_2$e using emission factors, fNRB, charcoal conversion ratios, and greenhouse-gas global warming potentials (GWPs). Some parameters straddle the line: the true fNRB in a project region is scientific, but the choice among spatial layers, defaults, and update frequency is a rulemaking choice.

Rulemaking connects the two. Approved methodologies determine which parameter values are permissible, whether measurement is required or defaults suffice, and how frequently science inputs must be updated. When approved frameworks permit parameter choices that overstate reductions—even relative to evidence available at the time—the resulting gap is structural, not operational.

**Table 1:** Sources of overcrediting across the voluntary carbon market.

| | | Threats to accurate crediting | | | | |
|---|---|---|---|---|---|---|
| **Sector** | **Crediting basis** | **Implementation** | **Rulemaking** | **Science** | **Credit est.[a]** | **Share[b]** |
| REDD+ | Avoided deforestation × carbon density | Site selection; low-threat boundaries | Developer-set baselines; no ex-post adjustment | Counterfactual deforestation rates | 8–14×[c] | 31% |
| Grid-scale renewables | Electricity generated × grid EF | Financial additionality at scale | Low thresholds; no reassessment as grid matures | Marginal vs. average dispatch | ∼3×[d] | 47% |
| Cookstoves | Fuel saved × EF × fNRB | Adoption/usage measurement; stove performance | Permissive fNRB (∼87% vs. 25–37%); default protocols | fNRB values; charcoal yields; rebound | 9.2→5.1×[e] | 10% |
| Industrial gases | Amount destroyed × GWP | Destruction monitoring; uptime | No production caps; credit value > abatement cost | — | —[f] | 7% |
| Energy efficiency | ΔEnergy use × EF | Consumption metering and verification | Deemed savings; no free-rider adjustment | Rebound (10–60%); technology degradation | 2–5×[g] | 4% |
| Waste & methane | $CH_4$ generated × capture − oxidized | Capture uptime; flare efficiency | Model defaults may overestimate | Oxidation rates; waste composition; decay kinetics | 1.5–3×[h] | 2% |

[a]Credit est. = ratio of credited to independently estimated reductions (>1 = overcrediting). [b]Credit shares from the voluntary market, 2020–2024[27]. [c]West et al.[4]: 7% additional; Tang et al.[13]: 13%. [d]Cames et al.[14]: 73% non-additional; Calel et al.[3]. [e]GKH[9] → this paper; 9.24× → 5.05× after corrections. [f]Overcrediting ratio not applicable: credit value exceeded abatement cost, incentivizing waste-gas overproduction rather than reduction[22;23]. EU banned HFC-23 credits in 2013. [g]Free-rider and rebound literature[28]. [h]Methane model comparisons[29].

## Definition-consistent evidence for cookstove crediting

GKH argue that projects systematically misreport the three behavioral parameters that drive credited savings: adoption (the share of distributed stoves still actively used), usage (the share of meals cooked on the project stove), and stacking (the share of meals cooked using both traditional and project stoves together). If true, this would mean overcrediting originates in implementation. But the claim depends entirely on the benchmarks used to judge project reports.

In the literature, these terms are not standardized. "Adoption" may mean any use within a week or being the primary stove; timing matters because equipment fails and substitutes exist. Stacking is defined at meal, day, or household scales. This heterogeneity requires evaluators to choose clear definitions and then use evidence consistent with those definitions.

GKH use the academic literature to benchmark adoption, usage, and stacking, under the assumption that well-measured projects should converge to published values. Treating project reports and research studies as directly comparable places substantial weight on literature selection and definitions. Given a heterogeneous evidence base, transparent search and inclusion rules are essential; GKH do not report a search strategy or inclusion criteria.

Of GKH's nine adoption studies, only five match their stated definition; the rest measure purchase rather than use, come from purposive low-uptake samples, or are untraceable (Fig. 2a; Table S1). Where values can be verified, GKH systematically select the lowest plausible estimate: Ruiz-Mercado et al. (2011)[35] are cited at 50% adoption though the study reports 90–95% active use; Burwen and Levine (2012)[36] are cited at 49% though the corrected figure is 65%. For usage, only one of nine citations measures the share of meals on the project stove (Fig. 2b; Table S2); none of the 24 stacking estimates capture simultaneous meal-level use (Fig. 2c; Table S3).

We screened more than 150 peer-reviewed studies identified from six systematic reviews[34;37–41], database searches, and citation chaining (Methods). We retained field studies with quantitative measures of adoption, usage, or stacking and excluded purely qualitative work, acquisition-only outcomes, and metrics not consistent with our (and GKH's) definitions. This yielded 60 adoption and 20 usage estimates (Tables S4, S5). No study reported the percentage of meals with simultaneous use of both stoves (GKH's stacking definition), but meal-share or cooking-minutes usage metrics implicitly capture most overlapping use.

# Meta-analytic benchmarks for adoption, usage, and stacking

We fit a random-effects meta-analysis (REMA) to the 60 adoption observations, using logit transformation and inverse-variance weights. Back-transforming, the fitted distribution yields a mean adoption of 0.75 and a median of 0.80 (IQR 0.63–0.91) (Fig. 2a–c), well above GKH's 0.55 from nine studies. For usage, the one study that matches GKH's rules reports 0.70 (vs. their 0.52). Extending the REMA to our 20 usage estimates yields a median of 0.55 (IQR 0.37–0.71), with a broader distribution than GKH's. Because no study measures simultaneous use of both stoves at the meal level, we apply a conservative 0–5% stacking discount to bound any residual overlap.

Independently, the CLEAR framework reaches a similar conclusion: projects without continuous household-level consumption tracking face a 10–25% discount on claimable Project Technology Days. Only projects that track consumption in every household can claim their measured behavioral parameters without discount.

# Fuel-use measurement and adjustment

Adoption and usage affect emissions only through how much less fuel each household burns. Fuel use is estimated by: (i) efficiency-based models using laboratory tests; (ii) direct, in-home measurement (KPTs or sensors); and (iii) back-calculation that infers baseline from project-period use assuming constant cooking services. Each produces natural-unit consumption (e.g., kg wood day$^{-1}$) for the same households, yielding baseline, project, and the difference that determines credited $CO_2$e.

To address noisy or implausible values, GKH impose a universal 2–4 MJ person$^{-1}$ day$^{-1}$ bound on both baseline and project use. While intended to manage outliers, a single band risks masking real heterogeneity: diet and simmer time, fuel type and moisture, climate, household size, and season all shift energy demand; reported values frequently lie outside this band[42–44]. Current methodologies do not require this bounding; all projects reported fuel use with accepted tools.

Applied to the 51-project sample (151 project-periods), GKH's constraint adjusts fuel values in a majority of observations, pushing most baselines down and project use up (Supplementary Table S6), cutting implied savings nearly in half—from 57% to 30% on average (excluding

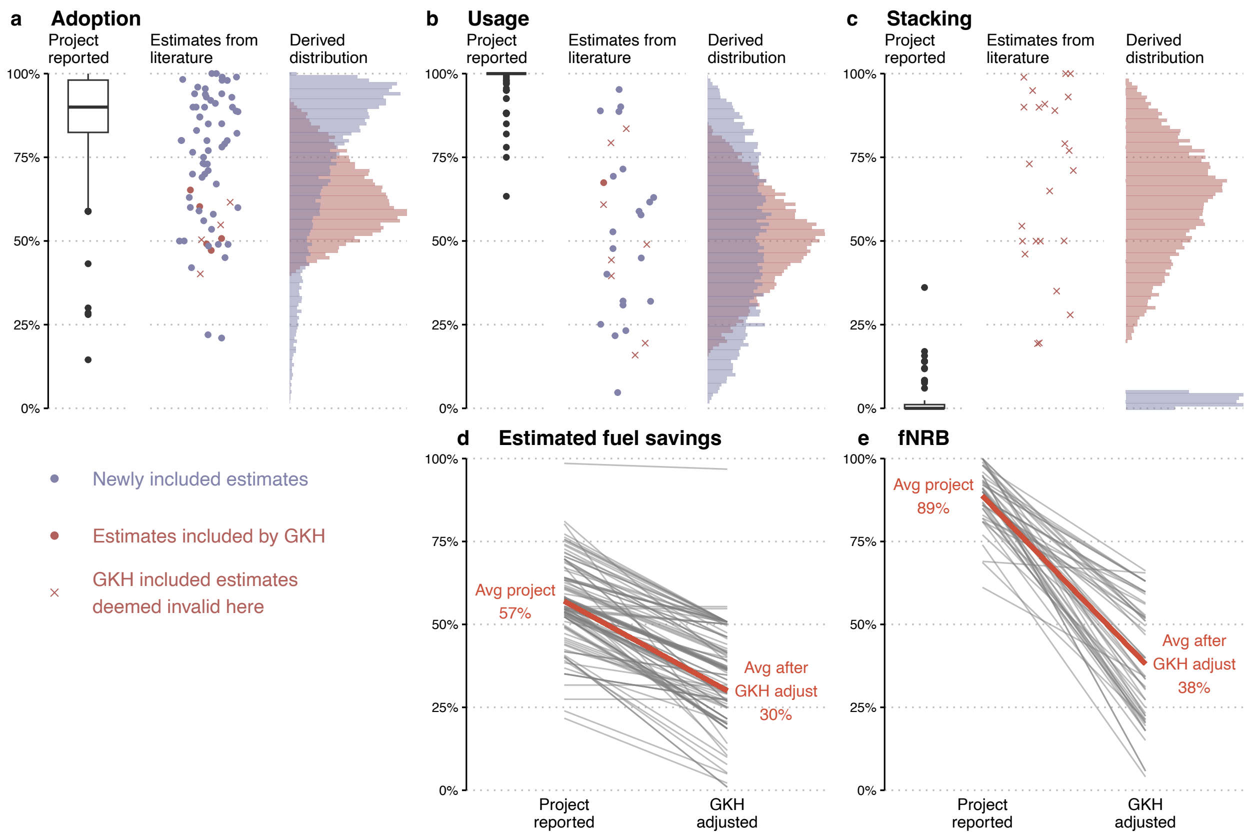


**Figure 2:** Widely used cookstove parameters in evaluations of the sector are biased low and poorly supported by evidence, and post hoc state-of-science references reduce credits. (a–c) Adoption, usage, and stacking estimates from GKH's literature review (red) compared to our expanded meta-analytic distributions (blue); shaded areas show the fitted logit-normal densities. (d) GKH's independent fuel bounds compress implied savings from 57% to 30% on average. (e) fNRB values used by projects (∼87.5%) versus Bailis et al. regional defaults (mean 25.5%).

fuel-switchers) (Fig 2d).

Bounding baseline and project consumption independently as GKH does ignores that both measurements come from the same households and instruments. When errors are shared, clamping each value independently biases the observed savings ratio. We therefore adopt a ratio-preserving approach: bound one period within 2–4 MJ person$^{-1}$ day$^{-1}$ and infer the other from the measured percent reduction (Methods). For example, baseline from 6 to 3 MJ person$^{-1}$ day$^{-1}$ (50% savings) becomes from 4 to 2, not from 4 to 3 (25%). If both periods require adjustment, we clamp baseline and project in turn, preserve the ratio in each case, and take the more conservative result.

The CLEAR framework imposes its own baseline fuel consumption bounds—a floor at 1.4 MJ person$^{-1}$ day$^{-1}$ (0.5 tonnes firewood person$^{-1}$ year$^{-1}$) and a cap at 5.3 MJ person$^{-1}$ day$^{-1}$ (2.0 tonnes person$^{-1}$ year$^{-1}$), with lower thresholds for charcoal. These are wider than GKH's 2–4 MJ band, and fewer than 10% of project-periods in our sample fall outside them.

## State-of-science parameters: why updates matter for crediting

Not all crediting inputs are under project control. Some describe physical conditions in a place and time and should be revised as evidence improves. The fraction of non-renewable biomass (fNRB) is the most consequential of these science parameters: it converts avoided firewood use into $CO_2$e, and has undergone substantial evolution over the past decade. Early practice often used national defaults of 80–90%[45]. With improved spatial datasets and models, many regions now exhibit markedly lower fNRB—at times one-third of earlier estimates and in some areas below 10%—reducing creditable savings[46;47]. Projects in our sample reported fNRB values averaging 87.5%, while the best available country-level estimates—whether from models available at the time (i.e., Bailis et al. (2015)) or more recent (Ghilardi et al. (2024)) spatial models—average ∼30% for the same countries. Modern methodologies favor region-specific, model-based values with a conservative 30% default where local evidence is lacking[18].

Charcoal yields tell a similar story. When wood is converted to charcoal in traditional kilns, a large share of the original energy is lost as heat and volatiles; the wood-to-charcoal conversion ratio—how many kilograms of wood produce one kilogram of charcoal—varies from 3:1 to more than 10:1 depending on kiln design, feedstock, and operating conditions[48;49]. Legacy methodologies routinely defaulted to 6:1. The CLEAR framework now requires region- and technology-specific yields where data exist, with a conservative 4:1 default when they do not (Methods). The largest projects in our sample use charcoal.

This evolution is not unique to cookstoves: avoided-deforestation standards have shifted to jurisdictional baselines using satellite data, and methane accounting now adopts updated IPCC global warming potentials[50–52]. In each case, the gap between what was credited and what occurred can widen even when nothing changed on the ground; in other words, the science moved, not project implementation.

## Evaluating cookstove carbon crediting

We reanalyze the 51 cookstove projects examined by GKH. Using the same cross-section, we ask: (i) does the headline replicate under the original rules? and (ii) conditional on replication, how much of the gap reflects choices projects control versus parameters that science has since updated?

We replicate their result (9.24×; 95% CI: 6.77–13.74; Fig. 3a,b). A coding correction has negligible effect (Methods).

Replacing GKH's literature selection with our meta-analytic distributions, and removing the post-hoc Hawthorne discount for protocols that directly measure household fuel use reduces the sample-wide discrepancy to 5.05× (95% CI: 3.72–12.47; Table S8). This is our best estimate of how already issued credits compare to actual reductions: projects claimed 27.1 Mt; we estimate roughly 5.4 Mt actually occurred, a shortfall of 21.7 Mt. Most of this gap traces to fNRB values projects reported.

Variation across projects is large. Several projects are indistinguishable from parity; a few exceed 50×. The median project-level ratio is 16× because a handful of large, well-calibrated charcoal projects pull the aggregate down. The five largest projects account for 74% of all verified credits; removing them raises the sector estimate by 30% (Fig. 3c).

Method and fuel interact. To separate the two, we estimate protocol effects conditional on fuel (Fig. 3d). Metered projects cluster near parity (1.4×). Charcoal under measurement-forward protocols tightens toward 2–3×; charcoal credited from defaults remains 5–6×; firewood shows a similar split. How outcomes are measured matters more than stove technology. Charcoal (75%) and firewood (19%) dominate issued credits, predominantly via legacy default-based pathways—the farthest from independent estimates.

Permissive parameter selection bears much of the blame. Projects selected fNRB values from the CDM tool averaging ∼87.5% when scientifically plausible regional estimates averaged less than half of that value—the rules permitted it, and most projects took it. Imposing the more favorable of the Bailis et al. regional estimate or a conservative 30% floor, with all other parameters at GKH's original values, reduces the ratio from 9.24× to 8.04× on its own.

What gap would remain if both credits and independent estimates were recalculated with the best available parameters? Under definition-consistent behavioral evidence, ratio-preserving fuel bounds, and updated fNRB, the ratio falls to 1.60× (95% CI: 1.21–3.60; Table S8)—the residual discrepancy if legacy projects were re-credited under CLEAR-like protocols. This residual is within the range of parameter uncertainty, consistent with a calibration problem rather than a structural one.

On a log scale, approximately two-thirds of the decline from 9.24× to 1.60× is attributable to science and rulemaking—principally permissive fNRB selection and its subsequent downward revision. The remaining third reflects implementation. Projects followed approved rules; most of the gap traces to what those rules permitted.

## Conclusion

Carbon crediting rests on three inputs that are routinely conflated: what projects do (implementation), what methodologies permit (rulemaking), and what science knows (state of the science). When the three are collapsed into a single overcrediting ratio, we cannot tell whether the gap reflects delivery and measurement, permissive rules, or updated physical parameters—problems that demand different fixes. A ninefold gap driven by projects selecting permissive defaults calls for tighter rules; a ninefold gap driven by science parameters revised after credits were issued calls for a system that updates those parameters on a schedule.

For cookstoves, the weak points center on behaviors that are hard to observe at scale. Historical discrepancies trace largely to measurement choices and restrictive priors. Projects that measure household fuel use align with independent benchmarks; projects that rely on defaults do not. Updating science inputs—principally fNRB—closes most of the remaining distance. Rule compliance is relevant to culpability, but not to the atmosphere: when credits are purchased as one-for-one offsets, what matters is whether the credited reduction occurred. At 5.05×, roughly 22 of the 27 Mt $CO_2$e these projects claimed to reduce did not actually occur.

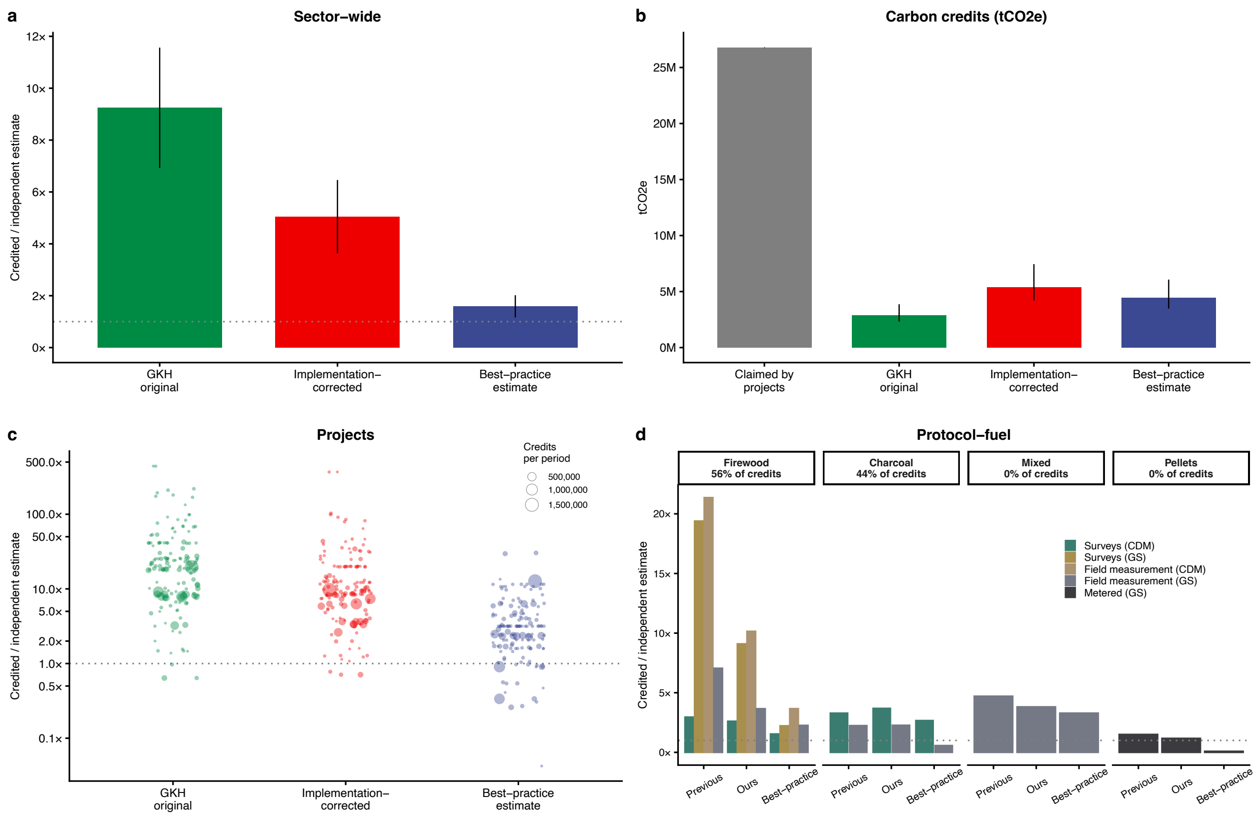


**Figure 3:** Alignment of cookstove project credited reductions with independent estimates: sector average, volumes, project dispersion, and protocol–fuel effects. (a) Sample-wide ratio of credited to independently estimated reductions: GKH's original estimate (9.24×), our atmospheric estimate after implementation corrections (5.05×), and our reform estimate under CLEAR-like protocols with max(Bailis, 30%) fNRB and ratio-preserving fuel bounds (1.60×). Bars show means; whiskers show 95% CIs from 10,000 Monte Carlo draws. (b) Aggregate $tCO_2e$ for the same 51-project sample: credits claimed by projects (27.1 Mt) and totals implied by each scenario. (c) Project-level ratios (y-axis, log scale) under the three scenarios; point size scales with a project's claimed credits. The dotted line denotes parity (1×). (d) Ratios by protocol–fuel category, highlighting method effects conditional on fuel. Colors distinguish measurement approaches (surveys/defaults vs. field measurement vs. metered) and standard (GS/CDM). Across panels, metered or field-measured projects cluster near parity, while default-permissive pathways remain several-fold high; updating fNRB further narrows gaps. Full model specifications appear in Supplementary Table S8.

Because most legacy cookstove credits were issued under the same default-based protocols and CDM fNRB tool values, the patterns we identify likely extend beyond our 51-project sample (15% of the ∼180 Mt issued to date[27]). If they do, roughly 140 Mt of credited $CO_2$e reductions never actually occurred. At recent estimates of the social cost of carbon (\$185 per $tCO_2$[53] to above \$1,000 per $tCO_2$[54;55]), the climate damages associated with that missing mitigation total \$27 billion–\$140 billion. The credits themselves sold for roughly \$1 billion, meaning that the climate damages from the missing mitigation are two to five orders of magnitude larger.

Who bears the responsibility for these errors? For the largest driver of overcrediting, fNRB, regional estimates were available when projects selected CDM tool values three times higher; in other words, better science existed and rules failed to require it. Projects themselves could have used the lower estimates, leading to fewer but more credible credits. For behavioral parameters, the remedy is not to substitute one set of external benchmarks for another—our meta-analytic estimates correct GKH's biased literature selection, but projects should measure their own adoption and usage directly rather than rely on any external prior. Protocols that reward continuous monitoring over surveys are the structural fix—and CLEAR's updated methodology penalizes projects that rely on surveys to estimate usage.

Analogues from other domains show how to treat scientific updates. In the Global Burden of Disease, estimates of air-pollution mortality for 2010 changed as methods and data improved; the series spans 6.8 million, 5.5 million, 6.4 million, 6.7 million, 7.8 million, and 7.5 million across successive releases[56]. We do not read this as a failure of integrity or the enterprise, but as science evolving. Crediting should work the same way: audit implementation in real time, update shared parameters on a schedule, and avoid retroactive penalties for good-faith delivery.

Legacy credits issued under generous defaults should not be purchased as tonne-for-tonne offsets. Buyers who wish to support cookstove projects could apply discounts consistent with the overcrediting ratio—purchasing five credits per tonne of claimed offset, for example—or treat these credits as contributions to clean-cooking access rather than as fungible emissions reductions.

Two fundamentals remain amid the controversy: real mitigation requires stoves that people want, can afford, and will use in ways that displace polluting fuels[16;30]; and among common carbon market strategies, clean cooking is the one most directly tied to human welfare.

Results-based climate finance functions when accounting keeps pace with evidence. Because this mechanism channels capital where other finance is scarce—to the 2.7 billion people who still lack access to clean cooking fuels—preserving it while improving accuracy is not optional. Systems that measure real behavior, apply current science, and update transparently can sustain trust and direct capital to verifiable climate and health gains. The tools now exist.

# Methods

We replicated and extended the analysis of Gill-Wiehl, Kammen, and Haya (2024; hereafter GKH), who evaluated credited emissions reductions from 51 improved cookstove projects using publicly available replication data and code (https://github.com/agillwiehl/GillWiehl_et_al_Pervasive_over_crediting). GKH compare reported project inputs to benchmark values drawn from academic literature and simulate counterfactual emissions reductions under those benchmarks. We make three modifications: (1) data corrections and implementation refinements; (2) reconstruction of benchmark parameter distributions from updated empirical evidence; and (3) sensitivity tests of modeling assumptions.

## Project sample and replication

We used the same dataset of 51 improved cookstove carbon crediting projects analyzed in GKH, covering firewood, charcoal, and ethanol stove interventions under four common offset methodologies (CDM AMS II.G, CDM AMS I.E, GS-TPDDTEC, GS Simplified, GS Metered) across 15 countries. These projects span more than a decade of crediting (2006–2019), during which methodology rules, registry standards, and available science all evolved. The dataset comprises 151 monitoring periods, with project-level data derived from project design documents: stove-days, reported adoption, usage, and stacking, baseline and project fuel consumption, emission factors, fNRB, firewood-to-charcoal conversion factors, and verified credits issued (Supplementary Table S7).

GKH simulate 10,000 realizations of emissions reductions for each project-period, drawing from parameter distributions for stove adoption, usage, stacking, fuel consumption, stove efficiency, rebound effects, fNRB, and fuel-switching assumptions. These simulated reductions are compared to project-reported reductions to calculate an overcrediting ratio. Ratios are weighted by stove-days and scaled by verified credits to produce project-level and sector-wide estimates. We retain GKH's Monte Carlo design (10,000 draws; `set.seed(4)`) throughout.

The full set of 23 model specifications, each varying one or more parameters relative to GKH's baseline, is documented in Supplementary Table S8.

**Correction of errors.** In replicating GKH's code and data, we identified two related implementation errors. First, GKH record 696 credits for project GS3112—the same value recorded for another project in the dataset, suggesting a copy error—when Verra registry records indicate >312,000 credits issued over the 2015–2019 period. Because GKH's code deduplicates by credit count, the duplicated value causes one record to drop from the numerator (reported credits) while its simulated counterfactual remains in the denominator, biasing the overcrediting ratio downward. Correcting both raises sector-wide overcrediting from 9.24× to 9.30×.

## Project-side parameters

**Evaluation of literature-derived adoption, usage, and stacking estimates.** We re-examined every adoption, usage, and stacking value cited by GKH. For each paper we recorded the variable actually measured, the recall or monitoring window, the sampling strategy, and the computation used to derive the statistic. Detailed annotations appear in Supplementary Tables S1–S3.

**Additional literature review.** To move beyond GKH's narrow evidence base, we assembled a candidate pool by aggregating all references contained in six prior systematic reviews, then supplemented these with targeted database searches and backward citation chaining. Title-and-abstract screening retained 152 peer-reviewed studies published before July 2025 that appeared to offer field data on adoption, usage, or stacking. We then applied four exclusion rules: the study had to (i) report quantitative outcomes, (ii) measure sustained use rather than promotional uptake (or purchase), (iii) identify households longitudinally, and (iv) present metrics that could be mapped cleanly onto our operational definitions. This pruning yielded 60 adoption and 20 usage estimates.

**Generating new parameter distributions.** Rather than adopt the triangular distributions used by GKH, we pooled estimates using random-effects meta-analysis in the `metafor` package in R. Adoption and usage proportions were logit-transformed, weighted by inverse sampling variance, and combined with restricted maximum likelihood. We drew 10,000 samples from each fitted distribution to propagate uncertainty through subsequent emissions calculations.

**Fuel consumption adjustments.** GKH impose a 2–4 MJ person$^{-1}$ day$^{-1}$ bound on both baseline and project fuel use independently, which can compress the observed savings ratio (Supplementary Table S6). Of the 111 non-excluded project-periods, 88 have firewood values adjusted under our V1 scenario (cap baseline, infer project from the measured ratio $r = (W_{\text{base}} - W_{\text{proj}})/W_{\text{base}}$) and 75 under V2 (cap project, infer baseline from $r$). Charcoal values are retained from GKH's species-corrected adjustments without further modification. Seventeen project IDs (40 periods) are excluded from ratio-preserving fuel adjustment because their raw fuel values encode conversion factors or other transformations that make the ratio meaningless (Supplementary Information).

**Rebound and monitoring reactivity.** GKH apply a uniform 22% rebound correction to emissions reductions. We instead apply rebound to fuel consumption (energy, MJ) and then reallocate to fuels proportionally by the project's fuel mix, which avoids double-counting when fuel compositions differ between baseline and project periods (Supplementary Methods). For protocols that measure household fuel use directly (GS-TPDDTEC, GS Metered), we adopt a measured-protocol rule: usage and stacking are already embedded in the measured fuel data, so we scale emissions by adoption only, without an additional Hawthorne/monitoring-reactivity discount.

## State-of-science parameters

**Charcoal yields.** We retain GKH's default 6:1 wood-to-charcoal conversion ratio in our baseline replication. Field measurements span 3:1 to more than 10:1 depending on kiln design and feedstock[48;49]; the CLEAR framework defaults to 4:1 where region-specific data are absent.

**Fraction of non-renewable biomass (fNRB).** To isolate implementation-linked parameters from science parameters, we fix fNRB at 30% for all projects, holding ecological context constant so that all remaining variation in overcrediting reflects project performance and monitoring.

**Max(Bailis, 30%) fNRB scenario.** To isolate the practice gap in fNRB selection, we construct a counterfactual in which each project uses the maximum of its Bailis et al. regional default and 30%—the better of best available science or a conservative floor. This scenario (Table S8, Models 15–17) asks: what if projects had selected the best available fNRB value rather than the CDM tool value, while everything else remained unchanged?

**Sensitivity to fNRB data source: Ghilardi et al. 2024.** Our main analysis uses Bailis et al. (2015) regional fNRB defaults as the independent reference, consistent with GKH. As a robustness check, we replace Bailis values with country-level MoFuSS-modeled fNRB estimates from Ghilardi & Bailis (2024)[47], the most recent spatially explicit fNRB assessment. Ghilardi values were mapped to projects via a 25-country crosswalk. Point estimates are very similar across both data sources (Supplementary Table S10).

## Aggregation and confidence intervals

Project-level overcrediting ratios are aggregated to a sector-wide estimate following GKH's procedure: $\mathrm{OC}_{\mathrm{sector}} = \sum_p \mathrm{VERs}_p \,/\, \sum_p (\mathrm{VERs}_p/\mathbb{E}[\mathrm{OC}_p])$, where $\mathrm{VERs}_p$ are verified credits and $\mathbb{E}[\mathrm{OC}_p]$ is the expected overcrediting ratio for project $p$. This credit-weighted harmonic formulation gives larger projects proportionally more weight. As a robustness check, we also compute stove-day-weighted (SDW) and ratio-of-sums (ROS) aggregates from the Monte Carlo draws; results are qualitatively similar.

Ninety-five percent confidence intervals are computed as the 2.5th and 97.5th percentiles of the 10,000 SDW sector-ratio draws. This quantile-based approach is more conservative than standard error-based intervals because the distribution of project-level overcrediting ratios is highly right-skewed.

## Decomposition

We use a Shapley value-based decomposition to attribute the gap between GKH's estimates and our updated estimates to implementation and science factors. Four scenarios are considered: (i) GKH replication ("Baseline"); (ii) Baseline plus only implementation updates; (iii) Baseline plus only science updates; and (iv) both sets together ("Both"). For each project, we log-transform the reported overcrediting ratio to treat multiplicative changes symmetrically, then average Shapley contributions across projects (Supplementary Decomposition).

## Code and data availability

All data and code used in this project will be made publicly available on Zenodo upon publication.

## Acknowledgements

We gratefully acknowledge helpful research assistance from Ricardo Piedrahita, Divyansh Agrawal, August Hughes, and Sarah Li. We appreciate helpful comments from Dana Charron, Ajay Pillarisetti, and Alex Heaney. We are additionally grateful to Annelise Gill-Wiehl and colleagues for making their data and code publicly available, facilitating this replication effort and open discussion. We acknowledge financial support from High Tide Foundation.

## Competing interests

Funding for this work was provided by the High Tide Foundation. Two of High Tide's founders/directors also co-founded and serve as directors of Proyecto Mirador, a clean cookstove project in Honduras. Proyecto Mirador appears in the dataset selected by GKH; we gave it no special attention in our methods or interpretation. The funder had no role in study design, data collection, analysis, interpretation, or the decision to submit the manuscript

# References

[1] Priyadarshi R. Shukla, Jim Skea, Raphael Slade, Alaa Al Khourdajie, Renée van Diemen, David McCollum, Minal Pathak, Shreya Some, Purvi Vyas, Roger Fradera, Malek Belkacemi, Apoorva Hasija, Géninha Lisboa, Sigourney Luz, and Juliette Malley, editors. *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, 2022. ISBN 978-92-9169-160-9. DOI: 10.1017/9781009157926.

[2] Benedict S. Probst, Malte Toetzke, Andreas Kontoleon, Laura Díaz Anadón, Jan C. Minx, Barbara K. Haya, Lambert Schneider, Philipp A. Trotter, Thales A. P. West, Annelise Gill-Wiehl, and Volker H. Hoffmann. Systematic assessment of the achieved emission reductions of carbon crediting projects. *Nature Communications*, 15(1):9562, nov 14 2024. ISSN 2041-1723. doi: 10.1038/s41467-024-53645-z.

[3] Raphael Calel, Jonathan Colmer, Antoine Dechezleprêtre, and Matthieu Glachant. Do Carbon Offsets Offset Carbon? *American Economic Journal: Applied Economics*, 17 (1):1–40, 1 2025. ISSN 1945-7782. doi: 10.1257/app.20230052.

[4] Thales A. P. West, Sven Wunder, Erin O. Sills, Jan Börner, Sami W. Rifai, Alexandra N.

Neidermeier, Gabriel P. Frey, and Andreas Kontoleon. Action needed to make carbon offsets from forest conservation work for climate change mitigation. *Science*, 381(6660): 873–877, aug 25 2023. doi: 10.1126/science.ade3535.

[5] Thales A. P. West, Jan Börner, Erin O. Sills, and Andreas Kontoleon. Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon. *Proceedings of the National Academy of Sciences*, 117(39):24188–24194, sep 29 2020. doi: 10.1073/pnas.2004334117.

[6] Joseph Romm, Stephen Lezak, and Amna Alshamsi. Are Carbon Offsets Fixable? *Annual Review of Environment and Resources*, 50(Volume 50, 2025):649–680, oct 6 2025. ISSN 1543-5938, 1545-2050. doi: 10.1146/annurev-environ-112823-064813.

[7] Philippe Delacote, Tara L'Horty, Andreas Kontoleon, Thales A. P. West, Anna Creti, Ben Filewod, Gwenole LeVelly, Alejandro Guizar-Coutiño, Ben Groom, and Micah Elias. Strong transparency required for carbon credit mechanisms. *Nature Sustainability*, 7(6): 706–713, 6 2024. ISSN 2398-9629. doi: 10.1038/s41893-024-01310-0.

[8] Nicolas Kreibich and Lukas Hermwille. Caught in between: credibility and feasibility of the voluntary carbon market post-2020. *Climate Policy*, 21(7):939–957, aug 9 2021. ISSN 1469-3062. doi: 10.1080/14693062.2021.1948384.

[9] Annelise Gill-Wiehl, Daniel M. Kammen, and Barbara K. Haya. Pervasive over-crediting from cookstove offset methodologies. *Nature Sustainability*, 7(2):191–202, 2 2024. ISSN 2398-9629. doi: 10.1038/s41893-023-01259-6.

[10] Fiona B Bennitt, Sarah Wozniak, Kate Causey, Sandra Spearman, Chukwuma Okereke, Vanessa Garcia, Nadim Hashmeh, Charlie Ashbaugh, Atef Abdelkader, Meriem Abdoun, et al. Global, regional, and national burden of household air pollution, 1990–2021: a systematic analysis for the global burden of disease study 2021. *The Lancet*, 405(10485): 1167–1181, 2025.

[11] Michael Greenstone. The Economics of the Global Energy Challenge. *AEA Papers and Proceedings*, 114:1–30, 5 2024. ISSN 2574-0768. doi: 10.1257/pandp.20241000.

[12] Rishikesh Ram Bhandary, Kelly Sims Gallagher, and Fang Zhang. Climate finance policy in practice: a review of the evidence. *Climate Policy*, 21(4):529–545, apr 21 2021. ISSN 1469-3062. doi: 10.1080/14693062.2020.1871313.

[13] Yuzhi Tang, Chao Yang, Haishan Wu, Zihao Xu, Linlin Tan, Wei Tu, Bowen Li, Zhaopeng Li, Zhijun Wang, Kai Guo, et al. Tropical forest carbon offsets deliver partial gains amid persistent over-crediting. *Science*, 390(6769):182–187, 2025.

[14] Martin Cames, Ralph O. Harthan, Jürg Füssler, Michael Lazarus, Carrie M. Lee, Pete Erickson, and Randall Spalding-Fecher. How additional is the Clean Development Mechanism? Analysis of the application of current tools and proposed alternatives. Technical report, Oeko-Institut and Stockholm Environment Institute, 2016. Study prepared for DG CLIMA, Reference: CLIMA.B.3/SERI2013/0026r.

[15] Philippe Delacote, Sylvain Chabé-Ferret, Anna Creti, Katharyn Duffy, Micah Elias, Alejandro Guizar-Coutiño, Ben Filewod, Ben Groom, Andreas Kontoleon, Gwenole LeVelly, Tara L'Horty, Anouch Missirian, and Thales A. P. West. Restoring credibility in carbon offsets through systematic ex post evaluation. *Nature Sustainability*, 8(7):733–740, 7 2025. ISSN 2398-9629. doi: 10.1038/s41893-025-01589-7.

[16] Joshua Rosenthal, Kalpana Balakrishnan, Nigel Bruce, David Chambers, Jay Graham, Darby Jack, Lydia Kline, Omar Masera, Sumi Mehta, Ilse Ruiz Mercado, Gila Neta, Subhrendu Pattanayak, Elisa Puzzolo, Helen Petach, Antonello Punturieri, Adolfo Rubinstein, Michael Sage, Rachel Sturke, Anita Shankar, Kenny Sherr, Kirk Smith, and Gautam Yadama. Implementation Science to Accelerate Clean Cooking for Public Health. *Environmental Health Perspectives*, 125(1), 1 2017. ISSN 0091-6765, 1552-9924. doi: 10.1289/EHP1018. [Online; accessed 2019-04-19].

[17] Joshua Rosenthal, Ashlinn Quinn, Andrew P. Grieshop, Ajay Pillarisetti, and Roger I. Glass. Clean cooking and the SDGs: Integrated analytical approaches to guide energy interventions for health and environment goals. *Energy for Sustainable Development*, 42:152–159, 2 2018. ISSN 09730826. doi: 10.1016/j.esd.2017.11.003.

[18] The Integrity Council for the Voluntary Carbon Market. Integrity Council approves three cookstove methodologies. https://icvcm.org/integrity-council-approves-three-cookstove-methodologies/, mar 7 2025. URL https://icvcm.org/integrity-council-approves-three-cookstove-methodologies/. [Online; accessed 2025-07-02].

[19] Annelise Gill-Wiehl, Marie Hogan, and Barbara K. Haya. Quantifying the additionality of cookstove carbon projects. *Carbon Management*, 17(1), 2026. doi: 10.1080/17583004.2026.2618350.

[20] Integrity Council for the Voluntary Carbon Market. The Core Carbon Principles. https://icvcm.org/core-carbon-principles/, 2023. URL https://icvcm.org/core-carbon-principles/. [Online; accessed 2025-08-11].

[21] Barbara K. Haya, Samuel Evans, Letty Brown, Jacob Bukoski, Van Butsic, Bodie Cabiyo, Rory Jacobson, Amber Kerr, Matthew Potts, and Daniel L. Sanchez. Comprehensive review of carbon quantification by improved forest management offset protocols. *Frontiers in Forests and Global Change*, 6, mar 21 2023. ISSN 2624-893X. doi: 10.3389/ffgc.2023.958879.

[22] Lambert Schneider and Anja Kollmuss. Perverse effects of carbon markets on HFC-23 and SF6 abatement projects in Russia. *Nature Climate Change*, 5(12):1061–1063, 12 2015. ISSN 1758-6798. doi: 10.1038/nclimate2772.

[23] Michael Wara. Is the global carbon market working? *Nature*, 445(7127):595–596, feb 7 2007. doi: 10.1038/445595a.

[24] Susanna B. Berkouwer and Joshua T. Dean. Credit, Attention, and Externalities in the Adoption of Energy Efficient Technologies by Low-Income Households. *American Economic Review*, 112(10):3291–3330, oct 1 2022. ISSN 0002-8282. doi: 10.1257/aer.20210766.

[25] Ther W. Aung, Grishma Jain, Karthik Sethuraman, Jill Baumgartner, Conor Reynolds, Andrew P. Grieshop, Julian D. Marshall, and Michael Brauer. Health and Climate-Relevant Pollutant Concentrations from a Carbon-Finance Approved Cookstove Intervention in Rural India. *Environmental Science & Technology*, 50(13):7228–7238, jul 5 2016. ISSN 0013-936X. doi: 10.1021/acs.est.5b06208.

[26] Tara Ramanathan, Nithya Ramanathan, Jeevan Mohanty, Ibrahim H. Rehman, Eric Graham, and Veerabhadran Ramanathan. Wireless sensors linked to climate financing for globally affordable clean cooking. *Nature Climate Change*, 7(1):44–47, 1 2017. ISSN 1758-678X, 1758-6798. doi: 10.1038/nclimate3141.

[27] Forest Trends' Ecosystem Marketplace. 2025 State of the Voluntary Carbon Market. Technical report, Forest Trends Association, Washington, DC, 2025. URL https://www.ecosystemmarketplace.com/publications/2025-state-of-the-voluntary-carbon-market-sovcm/. [Online; accessed 2025-09-10].

[28] Kenneth Gillingham, David Rapson, and Gernot Wagner. The Rebound Effect and Energy Efficiency Policy. *Review of Environmental Economics and Policy*, 10(1):68–88, jan 1 2016. ISSN 1750-6816, 1750-6824. doi: 10.1093/reep/rev017.

[29] Jeffrey Chanton, Tarek Abichou, Claire Langford, Gary Hater, Roger Green, Doug Goldsmith, and Nathan Swan. Landfill Methane Oxidation Across Climate Types in the U.S. *Environmental Science & Technology*, 45(1):313–319, jan 1 2011. ISSN 0013-936X. doi: 10.1021/es101915r.

[30] Meena Khandelwal, Matthew E. Hill, Paul Greenough, Jerry Anthony, Misha Quill, Marc Linderman, and H. S. Udaykumar. Why Have Improved Cook-Stove Initiatives in India Failed? *World Development*, 92:13–27, apr 1 2017. ISSN 0305-750X. doi: 10.1016/j.worlddev.2016.11.006.

[31] Kevin Mortimer and John R. Balmes. Cookstove Trials and Tribulations: What Is Needed to Decrease the Burden of Household Air Pollution? *Annals of the American Thoracic Society*, 15(5):539–541, may 1 2018. ISSN 2329-6933. doi: 10.1513/AnnalsATS.201710-831GH.

[32] Majid Ezzati and Jill C Baumgartner. Household energy and health: where next for research and practice? *The Lancet*, 389(10065):130–132, 1 2017. ISSN 01406736. doi: 10.1016/S0140-6736(16)32506-5.

[33] Evelyn A. Brakema, Rianne M. J. J. van der Kleij, Debbie Vermond, Frederik A. van Gemert, Bruce Kirenga, and Niels H. Chavannes. Let's stop dumping cookstoves in local communities. It's time to get implementation right. *npj Primary Care Respiratory Medicine*, 30(1):1–3, jan 10 2020. ISSN 2055-1010. doi: 10.1038/s41533-019-0160-8.

[34] Esther A Boudewijns, Maria Trucchi, Rianne M J J Van Der Kleij, Debbie Vermond, Charlotte M Hoffman, Niels H Chavannes, Onno C P Van Schayck, Bruce Kirenga, and Evelyn A Brakema. Facilitators and barriers to the implementation of improved solid fuel cookstoves and clean fuels in low-income and middle-income countries: an umbrella review. *The Lancet Planetary Health*, 6(7):e601–e612, 7 2022. ISSN 2542-5196. doi: 10.1016/s2542-5196(22)00094-8.

[35] Ilse Ruiz-Mercado, Omar Masera, Hilda Zamora, and Kirk R. Smith. Adoption and sustained use of improved cookstoves. *Energy Policy*, 39(12):7557–7566, dec 1 2011. ISSN 0301-4215. doi: 10.1016/j.enpol.2011.03.028.

[36] Jason Burwen and David I. Levine. A rapid assessment randomized-controlled trial of improved cookstoves in rural Ghana. *Energy for Sustainable Development*, 16(3):328–338, sep 1 2012. ISSN 0973-0826. doi: 10.1016/j.esd.2012.04.001.

[37] Daniel Pope, Michael Johnson, Nigel Fleeman, Kirstie Jagoe, Rui Duarte, Michelle Maden, Ramona Ludolph, Nigel Bruce, Matthew Shupler, Heather Adair-Rohani, and Jessica Lewis. Are cleaner cooking solutions clean enough? A systematic review and meta-analysis of particulate and carbon monoxide concentrations and exposures. *Environmental Research Letters*, 16(8):083002, 7 2021. ISSN 1748-9326. doi: 10.1088/1748-9326/ac13ec.

[38] Bipin Adhikari, Sophie Suh Young Kang, Aaryan Dahal, Salum Mshamu, Jacqueline Deen, Christopher Pell, Lorenz von Seidlein, Jakob Knudsen, and Thomas Chevalier Bøjstrup. Acceptability of improved cook stoves—a scoping review of the literature. *PLOS Global Public Health*, 5(1):e0004042, jan 7 2025. ISSN 2767-3375. doi: 10.1371/journal.pgph.0004042.

[39] David Dillon, Samara Reigh, Kristen M. Rappazzo, Thomas J. Luben, and Anne M. Weaver. A Systematic Review and Meta-Analysis Assessing the Impact of Improved Cookstove Technology Trials on Household Air Pollution and Human Health in Sub-Saharan Africa. *Current Environmental Health Reports*, 12(1):8, jan 28 2025. ISSN 2196-5412. doi: 10.1007/s40572-025-00476-9.

[40] Eunice Phillip, Jessica Langevin, Megan Davis, Nitya Kumar, Aisling Walsh, Vincent Jumbe, Mike Clifford, Ronan Conroy, and Debbi Stanistreet. Improved cookstoves to reduce household air pollution exposure in sub-Saharan Africa: A scoping review of intervention studies. *PLOS ONE*, 18(4):e0284908, apr 27 2023. ISSN 1932-6203. doi: 10.1371/journal.pone.0284908.

[41] Emma Thomas, Kremlin Wickramasinghe, Shanthi Mendis, Nia Roberts, and Charlie Foster. Improved stove interventions to reduce household air pollution in low and middle income countries: a descriptive systematic review. *BMC Public Health*, 15(1):650, jul 14 2015. ISSN 1471-2458. doi: 10.1186/s12889-015-2024-7.

[42] Nicholas Loren Lam, Basudev Upadhyay, Shovana Maharjan, Kirstie Jagoe, Cheryl L Weyant, Ryan Thompson, Sital Uprety, Michael A Johnson, and Tami C Bond. Seasonal fuel consumption, stoves, and end-uses in rural households of the far-western develop-

ment region of Nepal. *Environmental Research Letters*, nov 7 2017. ISSN 1748-9326. doi: 10.1088/1748-9326/aa98cc. [Online; accessed 2017-11-30].

[43] Charity Garland, Kirstie Jagoe, Emmy Wasirwa, Raphael Nguyen, Christa Roth, Ashwin Patel, Nisha Shah, Elisa Derby, John Mitchell, David Pennise, and Michael A. Johnson. Impacts of household energy programs on fuel consumption in Benin, Uganda, and India. *Energy for Sustainable Development*, 27:168–173, 8 2015. ISSN 09730826. doi: 10.1016/j.esd.2014.05.005.

[44] Rob Bailis, Victor Berrueta, Chaya Chengappa, Karabi Dutta, Rufus Edwards, Omar Masera, Dean Still, and Kirk R. Smith. Performance testing for monitoring improved biomass stove interventions: experiences of the Household Energy and Health Project. *Energy for Sustainable Development*, 11(2):57–70, 6 2007. ISSN 09730826. doi: 10.1016/S0973-0826(08)60400-7.

[45] Rob Bailis, Yiting Wang, Rudi Drigo, Adrian Ghilardi, and Omar Masera. Getting the numbers right: revisiting woodfuel sustainability in the developing world. *Environmental Research Letters*, 12(11):115002, 2017. ISSN 1748-9326. doi: 10.1088/1748-9326/aa83ed.

[46] Robert Bailis, Rudi Drigo, Adrian Ghilardi, and Omar Masera. The carbon footprint of traditional woodfuels. *Nature Climate Change*, 5(3):266–272, 3 2015. ISSN 1758-6798. doi: 10.1038/nclimate2491.

[47] Adrian Ghilardi and Robert Bailis. Updated fNRB Values for Woodfuel Interventions. Technical report, Zenodo, dec 6 2024. URL https://zenodo.org/records/14291479. DOI: 10.5281/zenodo.14291479.

[48] Ewunetu Tazebew, Shinjiro Sato, Solomon Addisu, Eshetu Bekele, Asmamaw Alemu, and Berhanu Belay. Improving traditional charcoal production system for sustainable charcoal income and environmental benefits in highlands of Ethiopia. *Heliyon*, 9(9): e19787, 9 2023. ISSN 24058440. doi: 10.1016/j.heliyon.2023.e19787.

[49] Jessie Urban, Jaden Berger, Yamungu Botha, Gloria Boafo-Mensah, Patience Agbedor, Aubrey Mkwate, Samuel Bentson, and Nordica A. MacCarty. Quantifying Charcoal Value Chain Conversion Factors in Malawi and Ghana. SSRN working paper. [Online; accessed 2025-09-09], 2025. URL https://papers.ssrn.com/abstract=5396738.

[50] IPCC. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/, 2019. URL https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventori [Online; accessed 2025-09-09].

[51] Integrity Council for the Voluntary Carbon Market. Integrity Council approves three REDD+ methodologies. https://icvcm.org/integrity-council-approves-three-redd-methodologies/, nov 15 2024. URL https://icvcm.org/integrity-council-approves-three-redd-methodologies/. [Online; accessed 2025-09-09].

[52] Daniel Conlon. U.S. EPA Releases Significant Update to AP-42 Section 2.4 for Solid Waste Landfills, aug 14 2025. URL https://www.all4inc.com/4-the-record-articles/u-s-epa-releases-significant-update-to-ap-42-section-2-4-for-solid-waste-landfill [Online; accessed 2025-09-09].

[53] Kevin Rennert, Frank Errickson, Brian C. Prest, Lisa Rennels, Richard G. Newell, William Pizer, Cora Kingdon, Jordan Wingenroth, Roger Cooke, Bryan Parthum, David Smith, Kevin Cromar, Delavane Diaz, Frances C. Moore, Ulrich K. Müller, Richard J. Plevin, Adrian E. Raftery, Hana Ševčíková, Hannah Sheets, James H. Stock, Tammy Tan, Mark Watson, Tony E. Wong, and David Anthoff. Comprehensive evidence implies a higher social cost of $CO_2$. *Nature*, 610:687–692, 2022. doi: 10.1038/s41586-022-05224-9.

[54] Adrien Bilal and Diego R. Känzig. The macroeconomic impact of climate change: global versus local temperature. *The Quarterly Journal of Economics*, page qjag011, 2026.

[55] Marshall Burke, Mustafa Zahid, Noah S. Diffenbaugh, and Solomon Hsiang. Quantifying climate loss and damage consistent with a social cost of carbon. *Nature*, 651:959–966, 2026. doi: 10.1038/s41586-026-10272-6.

[56] GBD 2021 Risk Factors Collaborators. Global burden and strength of evidence for 88 risk factors in 204 countries and 811 subnational locations, 1990–2021: a systematic analysis for the Global Burden of Disease Study 2021. *The Lancet*, 403(10440):2162–2203, 2024. doi: 10.1016/S0140-6736(24)00933-4.

# Supplementary Information

Aligning science, rulemaking, and practice to strengthen carbon crediting

Carlos F. Gould[1]

[1]School of Public Health, University of California San Diego.

Correspondence: cagould@health.ucsd.edu

# Contents

# S1 Review of GKH's included studies and their appropriateness for providing estimates of adoption, usage, and stacking

This section reviews each study included by Gill, Wiehl, and Hicks (hereafter GKH) in defining their triangular distributions for cookstove adoption, usage, and fuel stacking. For each study, we assess whether (a) the study design is appropriate for measuring the parameter in question, and (b) the parameter extracted by GKH is appropriate.

## S1.1 Adoption

Appendix Table S1 reproduces GKH's included studies for defining their adoption range, along with identifiers for reference. Here we review each study.

**[A1 Duflo]** is a randomized controlled trial conducted over several years in India. GKH identify an adoption rate of 40% after two years. This parameter extracted is inappropriate for defining adoption because of a mismatched study design. The basic design of the study centers not around the effects of an improved cookstove on socioeconomic and health outcomes, but around the effect of a lottery to have the opportunity to purchase an improved cookstove at a reduced rate. The authors identify the impacts of this lottery on outcomes, with randomization being used as an instrumental variable for the effectiveness of the improved cookstove. As such, only just over 70 percent of households that won one of the lotteries built a project stove during the first six months of the program. The data provided seek to answer the following research question: Among households in a village offered the opportunity to purchase an improved cookstove at a subsidized rate, how many had such a stove 36 months later as compared to the fraction of households in similar villages that were not offered a stove at the subsidized rate? Here, mismatched study design stems from the fact that not all households that were offered to purchase a stove did so. The 40% adoption parameter is drawn from a regression based proportion of households that were offered the opportunity to build a stove with an improved stove 25 to 30 months after offer.

**[A2 Burwen]** reports results after 8 months of a randomized controlled trial in Ghana. Adoption is inferred from field observations of households that did initially acquire an improved cookstove. Burwen report results in three categories: broken (not in use), appear in use, and unclear in use. GKH define adoption as the proportion of households that fall into the category "appear in use" out of all sampled households. This is an appropriate study and an appropriate parameter for adoption, though it is perhaps pessimistic because an alternative option would be to remove "unclear in use" from the denominator. Doing so would change adoption from 49% to 65%.

**[A3 Islam]** is a randomized controlled trial conducted over several years in India. GKH identify an adoption rate of 61.9% after two years. We are unable to identify where GKH find this parameter in the referenced article and thus are unable to determine its appropriateness.

**[A4 Beltramo]** is a randomized controlled trial conducted over several years in Uganda. This is an appropriate study and an appropriate parameter for adoption. Beltramo et al. report the impacts of an improved cookstove on fuel use and pollution. Study enumerators then made unannounced visits three and a half years later, finding that 65% of households had a project stove with obvious signs of use. Beltramo et al. also measure project stove use within the first year of stove acquisition, which are expected to be higher than 65% adoption, though they do not provide clear adoption-related measures as they for their long-term follow up. We believe that GKH make a small math error. The calculation should yield an estimate of 67% adoption (instead of 65%). An alternative option would have been 73% self-reported to still use the Envirofit after 3.5 years.

**[A5 Rosa]** is a randomized controlled trial conducted among 566 households in Rwanda conducted over five months assessing the combined impacts of a water filter and an improved biomass cookstove on children's respiratory health. This article reports on the impacts on drinking water quality and household air pollution. GKH report an adoption rate of 47.5% over six months. Rosa et al. report data on cookstove use in several different ways. They report data from "Evaluator's surveys"—these are surveys collected by the researchers—as well as data from "Implementer's surveys"—surveys collected by the project implementers. GKH report data from the Evaluator's surveys, which is a fair choice under the assumption that researchers might be more likely to produce least biased estimates (though both surveys yield similar results). Rosa et al. report data separately among households that were actively cooking while the survey visit occurred from those that were not cooking. GKH report data from those that were not actively cooking, which is a fair choice. Next, Rosa et al. report whether the household reported to have used only the intervention stove (78%), both the intervention and traditional stove (19.3%), or only the traditional stove for their last stove use (2%). They also report whether the intervention stove was reported to have been used in all three of the last follow-up visits (47.5%). It is clear that GKH opt for this last parameter as their measure of adoption. Plausibly, GKH could have also identified adoption as 98%, where adoption is identified from reporting to have used the intervention stove during their last meal. The implementer's survey is more extensive, and reports that 89.1% of households identified the intervention stove as their primary stove and 93.3% report using it 7 or more times per week. Taken together, we deem GKH's parameter extraction as appropriate and the study design is also appropriate, but the parameter extraction is also pessimistic.

**[A6 Ruiz-Mercado]** is a long term monitoring study of plancha stoves in Mexico. We are unable to identify where GKH identify an adoption rate of 50% after 10 months. The parameter extracted does not appear appropriate, though the study design is appropriate. The authors report that, after 2.6 years, 90% of stoves are still used on a daily basis (section 4.1.1, Figure 3). After three months, 95% of households responded yes to "Are you using the Plancha for cooking?" (Figure 4A). We identify two plausible data points that led GKH to extract 50% adoption rates. First, the authors report data from an initial sample of 50 households during the initial adoption stage. Second, the authors identify that half of households continued using their traditional stoves in the long term.

**[A7 García-Frapolli]** reports results on adoption from a different study Pine et al. 2010, but no new primary data are reported. It is not clear why GKH cite García-Frapolli instead of Pine et al. 2010. Here, we discuss Pine et al., who report results from a quantitative longitudinal study of households in Mexico. GKH identify an adoption rate of 60% after two to seven years. In their Figure 2, Pine et al. report that 60% of households used their stove, defined as any reported use of the Patsari at month five, with Figure 3 reporting similar levels of any Patsari use at month 10. Plausibly these data points match GKH's definition of adoption. With that said, Pine et al. also write "Of the 259 households in the sample, 10% or 26 of the 259 did not adopt the Patsari stove at all" and ". . . some (17%) of the households ultimately rejected the technology by the end of the 10 month follow-up period." We are unable to identify where GKH derive their 2–7 year time frame. There is some lack of clarity as to what Pine et al. refer to when they indicate that 10–17% of households rejected the technology, but that reported usage was closer to 60% of households. GKH report the 60% figure for adoption, though one could imagine also reporting 83% adoption based on this study. Ultimately, we deem that the parameter extracted is appropriate and the study design is appropriate, though the extraction of these parameters over others is perhaps pessimistic.

**[A8 Adrianzén]** is a cross-sectional observational study in the northern Peruvian Andes. GKH identify an adoption rate of 55% after 10 months. The parameter extracted is not appropriate for defining adoption and the study design is not appropriate. First, this cross-sectional study purposefully identified a sample "where relatively low usage rates were expected." As such, it is inherently a downward biased estimate. Second, in their Table 1, Adrianzén report data on the proportion of visited beneficiaries in a village that received their improved stove but were not making use of it. The average was 55%. We believe that this is where GKH defined their adoption, erroneously interpreting the table. Were the study design to have been appropriate, GKH should have extracted an adoption rate of 45%. Adrianzén further clarify in text: "Table 1 also indicates that approximately 45% of the visited beneficiaries per village reported using the new stove as their main cooking device."

**[A9 Bensch]** is a randomized controlled trial conducted in rural Senegal. GKH identify an adoption rate of 51% after 3.5 years. The study design is appropriate and the parameter extracted is appropriate for defining adoption, although it may be pessimistic. The authors report that the expected lifetime of the stoves was one to three years. As such, adoption beyond that expected lifetime is anticipated to be low. The authors write: "Considering an expected life span of one to three years, the proportion of 49% of treatment households still using the randomized ICS can, nevertheless, be considered surprisingly high." Note a small error from GKH in reporting adoption of 51% instead of 49% after 3.5 years. Bensch's Figure 4 reports the proportion of households still using the project stove by month. At their initial follow-up, Bensch reports that there are only 2 households out of 253 that do not use the project stove. Plausibly, adoption could have been identified as 99%.

**Table S1:** Adoption rates from academic literature used by GKH. Adoption rates listed here reflect values reported by GKH unless otherwise noted.

| ID | Study Title | Country | Time (yr) | Adopt. | Year | *n* | Stove Type |
|---|---|---|---|---|---|---|---|
| A1 | Up in smoke: The influence of household behavior on the long-run impact of improved cooking stoves | India | 2 | 0.40 | 2016 | 2,650 | Improved biomass stove with chimney |
| A2 | A rapid assessment randomized-controlled trial of improved cookstoves in rural Ghana | Ghana | 0.67 | 0.49 | 2023 | 164 | Envirofit improved biomass stove |
| A3 | Assessing the Effects of Stove Use Patterns and Kitchen Chimneys on Indoor Air Quality during a Multiyear Cookstove RCT in Rural India | India | 3.5 | 0.619 | 2022 | 480 | Improved biomass chimney stove, LPG |
| A4 | The Effects of Fuel-Efficient Cookstoves on Fuel Use, Particulate Matter, and Cooking Practices: Results from a Randomized Trial in Rural Uganda | Uganda | 3.5 | 0.65 | 2024 | 955 | Improved charcoal stove |
| A5 | Assessing the Impact of Water Filters and Improved Cook Stoves on Drinking Water Quality and Household Air Pollution: A RCT in Rwanda | Rwanda | 0.5 | 0.475 | 2014 | 566 | EcoZoom Dura improved biomass stove |
| A6 | Quantitative metrics of stove adoption using Stove Use Monitors (SUMs) | Guatemala | 0.83 | 0.50 | 2013 | 80 | Plancha chimney stove |
| A7 | Beyond fuelwood savings: Valuing the economic benefits of introducing improved biomass cookstoves in the Purépecha region of Mexico | Mexico | 2–7 | 0.60 | 2010 | 232 | Patsari improved biomass cookstove |
| A8 | Social Capital and Improved Stoves Usage Decisions in the Northern Peruvian Andes | Peru | 0.83 | 0.55 | 2010 | ∼275 | Iron-frame biomass stove with chimney |
| A9 | The intensive margin of technology adoption: Experimental evidence on improved cooking stoves in rural Senegal | Senegal | 3.5 | 0.51 | 2014 | 1,000 | Low-cost portable clay-metal improved biomass stove |

## S1.2 Usage

GKH largely draw on a previous review—Jeuland et al.—for their identification of usage rates. They additionally include one other study. While not explicitly referenced in GKH's appendix or elsewhere, we believe this study is Ruiz-Mercado (2012).

**[U1 Rosa]** is a randomized controlled trial conducted over several years in Rwanda. It is the same as [A5 Rosa]. This parameter extracted is inappropriate for defining usage because it more closely matches GKH's definition for adoption.

**[U2 Ruiz-Mercado]** The study by Ruiz-Mercado et al. (2012) uses Stove Use Monitors (SUMs) to measure stove usage in 80 rural Guatemalan households over 32 months. The study defines usage metrics based on daily stove use, counting the percentage of days in use, the number of meals cooked per day, and the total stove-hours recorded. The reported usage rate of 50% refers to the percentage of monitored stoves actively in use during the study period. While the study tracks sustained stove use, it does not directly quantify how often traditional stoves are used for meal preparation versus the improved stove, which is critical for GKH's definition. Therefore, this measurement method does not fully align with GKH's definition of usage rate.

**[U3 Hanna]** is the same as [A1 Hanna]. This parameter extracted is inappropriate for defining usage. Please see above discussion under the adoption section for an explanation of the study design, and its lack of suitability for adoption and also usage.

**[U4 Traction]** is an unknown study.

**[U5 García-Frapolli]** is a study that focuses on the costs and benefits of the Patsari Cookstove among Purépecha regions. The study disseminated 1,672 Patsari stoves to randomly selected households from 2003 to 2008. The study found that "60% or 1,003 stoves were being used on a sustained long-term basis." This study design is inappropriate for defining usage because it lacks meal-specific tracking or measures of total stove use completed by the project stove.

**[U6 Adrianzén]** This study examines the role of social capital in the adoption and usage of improved cookstoves in the Northern Peruvian Andes. The reported usage rate of 45% was determined through household surveys conducted 8–12 months after stove distribution, where beneficiaries self-reported whether they used the improved stove as their primary cooking device. This study design is inappropriate for defining usage because it lacks meal-specific tracking or measures of total stove use completed by the project stove.

**[U7 Bensch]** is a randomized controlled trial conducted from 2009 to 2013. The study employs various measurement methods, including household surveys, firewood measurement, and health indicators, to evaluate the effectiveness of a low-cost, maintenance-free portable clay-metal stove (ICS) and its impact on health. The study reports a utilization rate of 69.1% among the treatment group using the ICS at follow-up. The parameters and study design are appropriate for accurately measuring the usage rate.

**[U8 Traction]** is an unknown study.

**[U9 Ruiz-Mercado]** It is unclear how GKH's reported 85% usage rate was determined. The study primarily focuses on measuring the sustained use of improved cookstoves using stove use monitors. The key metric presented by Ruiz-Mercado is the "percent stove-days in use," which quantifies the number of days the improved stove was used relative to the monitoring period. However, GKH's definition of usage rate would require clear data on the proportion of total cooking done on the improved stove versus the traditional stove. Since this study does not explicitly quantify the continued use of traditional stoves or the proportion of meals cooked on them, it is inappropriate for defining usage.

**Table S2:** Usage rates from academic literature used by GKH.[a]

| ID | Study Title | Country | Time (yr) | Usage Rate |
|---|---|---|---|---|
| U1 | Assessing the Impact of Water Filters and Improved Cook Stoves on Drinking Water Quality and Household Air Pollution: A RCT in Rwanda | Rwanda | 0.5 | 0.80 |
| U2 | Adoption and sustained use of improved cookstoves | Mexico | 0.83 | 0.50 |
| U3 | Up in smoke: The influence of household behavior on the long-run impact of improved cooking stoves | India | 2 | 0.40 |
| U4 | Unknown | India | Unknown | 0.20 |
| U5 | Beyond fuelwood savings: Valuing the economic benefits of introducing improved biomass cookstoves in the Purépecha region of Mexico | Mexico | 2–7 | 0.60 |
| U6 | Social Capital and Improved Stoves Usage Decisions in the Northern Peruvian Andes | Peru | 0.83 | 0.45 |
| U7 | The intensive margin of technology adoption: Experimental evidence on improved cooking stoves in rural Senegal | Senegal | 3.5 | 0.69 |
| U8 | Unknown | India | Unknown | 0.16 |
| U9 | The Stove Adoption Process: Quantification Using Stove Use Monitors (SUMs) in Households Cooking with Fuelwood | Guatemala | 2.67 | 0.85 |

[a] Studies U1–U8 are from Jeuland et al. whereas study U9 is added by GKH.

## S1.3 Stacking

Recall that GKH define stacking as the percentage of meals where the traditional stove and the project stove are used in tandem. We review specific studies cited by GKH for their ranges of stacking and whether they meet this definition.

**[S1 Asante]** report data that are now published under the title "Experiences with the Mass Distribution of LPG Stoves in Rural Communities of Ghana" by Carrion et al. This study is a cross-sectional that reports that, after 9 months, less than 5% of households used LPG for cooking their main meals the previous day based on self-reported survey data. GKH cite a stacking rate of 100%. Given the data reported in Carrion et al., this is not appropriate because their reported data do not match GKH's definition of stacking.

**[S2 Pollard]** This study evaluates Peru's Fondo de Inclusión Social Energético (FISE) program, which promoted the adoption of liquefied petroleum gas (LPG) through a voucher system subsidizing half the cost of one LPG cylinder per month for eligible households. The study reports a stacking rate of 95%, which was determined through household surveys conducted in rural Puno, where participants self-reported their stove use patterns. This study's approach captures whether households used multiple stoves within a given period but does not track whether both stoves were actively used together for the same meal; therefore, the reported stacking rate is inconsistent with GKH's definition.

**[S3 Gould]** This study is a cross-sectional observational study that reports a stacking rate of 79%, with households in a very rural area of Ecuador using woodfuel weekly or more frequently despite having LPG stoves. The stacking rate of 79% comes from the survey data indicating that woodfuel is frequently used as a secondary fuel, with 86% of households using woodfuel alongside LPG. GKH cite this stacking rate based on the survey data that measures woodfuel use. However, this is not appropriate because the measure used—reporting woodfuel use weekly or more frequently—does not align with GKH's definition of stacking, which focuses on the concurrent use of traditional and project stoves for cooking meals.

**[S4 Thoday]** The study by Thoday, which reports a stacking rate of 73% in various provinces of Indonesia, calculates this rate using survey questions like "Which stoves have you used in the last three days?" and "List all stoves you have in the household." The 73% stacking rate indicates that a majority of households are using multiple stoves, including both LPG and traditional stoves. However, this measurement doesn't align with GKH's definition of stacking, which focuses specifically on the percentage of meals where both traditional and project stoves are used simultaneously.

**[S5–S6 Bruce]** This study evaluates the government-led initiative for LPG scale-up in Cameroon. The reported stacking rates of 90% and 99% were derived from household surveys conducted in peri-urban and rural areas, as part of the LPG Adoption in Cameroon Evaluation (LACE) studies. The survey questions focused on whether households used multiple fuels and how often LPG was refilled. Since the reported stacking rates were found through self-reported fuel use surveys and refill frequency data, which indicate continued use of traditional stoves but do not capture concurrent stove usage during meal preparation, this measure does not align with GKH's definition of stacking.

**[S7 Ozier]** This study evaluates a commercial pilot program promoting ethanol-methanol CleanCook stoves in Lagos, Nigeria. The reported stacking rate of 65% was determined through a combination of household surveys, stove use monitors, and fuel canister sales data collected from 30 experimental households over five months. The surveys asked households whether they continued using traditional stoves, while stove use monitors (SUMs) tracked temperature changes as a proxy for use. This study's approach to measure stacking captures overall stove usage patterns over time rather than whether both stoves were actively used together for the same meal; therefore, it does not match GKH's definition of stacking.

**[S8 Benka-Coker]** This study is a randomized controlled trial and pilot study that reports a stacking rate of 65% in Lagos, Nigeria, where CleanCook ethanol-methanol stoves were introduced. GKH cite this stacking rate based on a combination of surveys and stove use monitors, which show households using both CleanCook stoves and traditional stoves. However, this measure is uncertain in terms of fully aligning with GKH's definition of stacking, as it is based on indirect indicators like fuel canister usage rather than directly measuring the percentage of meals cooked using both stove types in tandem.

**[S9 Carter]** In the study by Carter et al., the reported stacking rate of 77% in southwestern China is based on a before-and-after intervention that introduced semi-gasifier stoves and biomass pellets. This rate was calculated by observing the continued use of traditional wood chimney stoves alongside the new stoves. However, this measure reflects general stove usage over time rather than concurrent use during meal preparation, which is how GKH defines stacking. Therefore, it is not appropriate for use as a metric for tracking stacking.

**[S10–S12 Clemens]** This study is a cross-sectional one-time survey that reports a stacking rate of 46% in Kenya, where households with biodigesters use both biogas and traditional fuels for cooking. GKH cite this stacking rate based on data showing that while 54% of households use biogas exclusively, 46% stack biogas with other fuels. However, this is not appropriate because the measure used—percentages of households exclusively or partially using biogas—does not align with GKH's definition of stacking, which focuses on the concurrent use of traditional and project stoves for cooking meals.

**[S13–S14 Hyman]** This study evaluates a national biodigester program in Cambodia and reports two stacking rates: 28% and 50%. The stacking rate was determined through household surveys and stove use monitors, which tracked household fuel use and cooking patterns. Surveys asked respondents about their primary and secondary stove use, while stove use monitors recorded temperature fluctuations on traditional and biodigester stoves as a proxy for stove usage. Additionally, observational data collected from a subset of households indicated that while biogas was used for primary cooking, many households continued to rely on traditional stoves, particularly for cooking tasks requiring high heat or large pots. Therefore, since the reported stacking rate in this study was found through a combination of survey self-reports and indirect monitoring methods that did not specifically capture simultaneous stove use during meal preparation, it does not meet GKH's definition.

**[S15 Rosa]** This is a parallel household RCT conducted over a year in three rural villages in Rwanda. The study reports a stacking rate of 19.3% among 585 participating households. This rate does not align with GKH's definition because it reflects the percentage of households using traditional and improved cooking stoves together during the study, rather than the percentage of meals prepared with both stoves. Additionally, the 19.3% stacking rate is different from the researchers' observations, where only 4.3% of households used both stoves simultaneously during their visit.

**[S16–S17 Ruiz-Mercado]** Reports data from a Master's thesis by Zamora. This study uses sensor-based monitors to observe the adoption process and impacts of the improved cookstove program implemented in Purepecha and Mestizo villages in Mexico. The study reports a stacking rate of 90% among Purepecha participants, indicating that "90% now stack the TSF with Patsaris, LPG stoves, and microwaves (MW)." It also reveals a stacking rate of 50% among Mestizos, who "continue using the three-stone fire (TSF) with gas (LPG) stoves and even microwaves (MW)." These stacking rates do not meet GKH's definition because they focus on overall usage across households, rather than within households from meal to meal. We note that GKH report these race/ethnic group stratification statistics in reverse.

**[S18 Hanna]** This study evaluates the long-term effects of an improved cookstove intervention in India, examining behavioral patterns and sustained use of traditional stoves. The reported stacking rate of 93% was derived from household surveys and direct observations conducted over a two-year period. Surveys captured self-reported stove usage, while field observations tracked cooking behaviors in randomly selected households. Since the reported rate primarily reflects stove ownership and continued use rather than the percentage of meals cooked using both traditional and project stoves in tandem, it does not match GKH's definition of stacking.

**[S19 Bensch]** This is a randomized controlled trial conducted in rural Senegal from 2009 to 2013. The study evaluates the usage of improved cookstoves and their potential impacts on participants' health. Based on surveys of 253 randomly selected households, the study reports that 19.5% of the treatment group continue to use open fires (three-stone stoves or open fires) for cooking. This data suggests that the treatment group "stacks" project stoves with open-fire stoves. However, this data does not exactly reflect concurrent stove usage during meal preparation, but it rather provides a general overview of stove usage patterns among households. Therefore, it does not meet GKH's definition of stacking.

**[S20 Pattanayak]** This is a multiphase randomized controlled study assessing the implementation and adoption of improved biomass stoves and LPG stoves. It involves about 1,000 households from the Indian Himalayas. The study does not explicitly discuss the stacking rate, but it does report that the treatment group had an average daily use of 231.6 minutes for traditional cooking stoves (TCS) three months after the intervention. Additionally, the supplementary information indicates that 26.6% of the control group and 54.5% of the treatment group used improved stoves in the past week. However, this measure is not an appropriate parameter for stacking. It does not meet GKH's definition, which focuses on the concurrent use of project stoves and traditional stoves.

**[S21 Pine]** This study evaluates the adoption and sustained use of Patsari improved biomass cookstoves in rural Mexico. The reported stacking rate of 35% was determined through a combination of structured household surveys, follow-up interviews, and observational data. Households were classified into different stove usage groups based on self-reported cooking practices and physical evidence of stove use gathered during home visits. The study captures broader patterns of stove use over time without explicitly tracking concurrent use for the same meal; therefore, it does not match GKH's definition which requires measuring the percentage of meals where both stoves are used simultaneously.

**[S22 Burwen]** This is a randomized controlled study conducted in rural Ghana that examines the impacts of improved cookstoves. The study uses stove usage monitors, field observations, and self-reported surveys. The results show that the treatment group uses the improved cookstoves more frequently than traditional cookstoves but continues to use the traditional ones during their cooking events. The stove usage monitors indicate that "50% of improved cookstoves remained in use" within the treatment group. However, this measure is not an appropriate parameter for stacking and does not meet GKH's definition of stacking.

**[S23 Beltramo]** This study is a randomized controlled trial conducted in Uganda that assesses the impact of fuel-efficient cookstoves on fuel use, particulate matter exposure, and cooking behaviors. The study reports a stacking rate of 90.9%, which was determined through a combination of self-reported surveys and temperature-based stove use monitoring. Households were given improved cookstoves, and researchers tracked their cooking behaviors using stove use monitors, which recorded temperature fluctuations to infer stove usage. However, this measure does not align with GKH's definition of stacking, which focuses on the percentage of meals where both the traditional and project stoves are used in tandem.

**[S24 Ruiz-Mercado]** The study by Ruiz-Mercado et al. evaluates the sustained adoption and usage patterns of improved cookstoves in rural Guatemala. The reported stacking rate of 50% is derived from stove use monitors, which recorded temperature fluctuations in 80 households over 32 months. The SUMs tracked daily cooking events, defining "fueling events" based on temperature spikes, which were clustered into cooking events or "meals." The study found that while 90% of stove-days involved the use of the improved chimney stove, 50% of households continued to use open cookfires alongside it. The reported stacking rate in this study was found through general household-level stove usage patterns, meaning it captures whether a household continued using both stoves but does not specify if both were used for the same meal; therefore, this measure does not align with GKH's definition of stacking.

In summary, none of the 24 stacking values cited by GKH directly measure the parameter they define—the percentage of meals where both stoves are used in tandem. Most studies report household-level indicators of continued traditional stove use, which conflates stacking with adoption failure and yields systematically higher stacking rates. GKH's triangular distribution, Triangular(0.193, 0.99, 0.673), with a mode of 67%, therefore substantially overestimates the fraction of meals where fuel savings are negated by concurrent traditional stove use.

**Table S3:** Stacking rates cited by GKH and their definitional alignment.

| ID | Study Title | Rate | Definitional Assessment |
|---|---|---|---|
| S1 | Asante (Carrion et al.) – Ghana | 100% | Does not match |

**Table S3:** Stacking rates cited by GKH. *(continued)*

| ID | Study Title | Rate | Definitional Assessment |
|---|---|---|---|
| S2 | Pollard – Peru (FISE) | 95% | Does not match |
| S3 | Gould – Ecuador | 79% | Does not match |
| S4 | Thoday – Indonesia | 73% | Does not match |
| S5 | Bruce – Cameroon (peri-urban) | 90% | Does not match |
| S6 | Bruce – Cameroon (rural) | 99% | Does not match |
| S7 | Ozier – Nigeria (Lagos) | 65% | Does not match |
| S8 | Benka-Coker – Ethiopia | 100% | Does not match |
| S9 | Carter – China | 77% | Does not match |
| S10 | Clemens – Kenya | 46% | Does not match |
| S11 | Clemens – Tanzania | 71% | Does not match |
| S12 | Clemens – Uganda | 89% | Does not match |
| S13 | Hyman – Cambodia (a) | 28% | Does not match |
| S14 | Hyman – Cambodia (b) | 50% | Does not match |
| S15 | Rosa – Rwanda (RCT) | 19.3% | Does not match |
| S16 | Ruiz-Mercado – Mexico (Purepecha) | 50% | Does not match |
| S17 | Ruiz-Mercado – Mexico (Mestizo) | 90% | Does not match |
| S18 | Hanna – India | 93% | Does not match |
| S19 | Bensch – Senegal (RCT) | 19.5% | Does not match |
| S20 | Pattanayak – India (Himalayas) | 54.5% | Does not match |
| S21 | Pine – Mexico (Patsari) | 35% | Does not match |
| S22 | Burwen – Ghana (RCT) | 50% | Does not match |
| S23 | Beltramo – Uganda (RCT) | 90.9% | Does not match |
| S24 | Ruiz-Mercado – Guatemala (SUMs) | 50% | Does not match |

# S2 Expanded literature review

To address the limitations identified in Section S1, we conducted a systematic literature search to obtain updated estimates of cookstove adoption and usage rates. Our expanded review identifies 60 studies reporting adoption rates and 20 studies reporting usage rates, compared to GKH's 9 studies for each parameter. We fit meta-analytic logit-normal distributions using random-effects models (DerSimonian-Laird / REML) rather than the triangular distributions used by GKH.

For stacking, we replace GKH's Triangular(0.193, 0.99, 0.673) distribution with a Uniform(0, 0.05) distribution, as a reflection that residual fuel stacking – as defined here – is minimal.

**Table S4:** Adoption rates drawn from the academic literature used in this study. "Adoption" is the primary estimate; "Alt" is an alternative estimate where available.

| Author-Year | Stove | *N* | Adopt. | Alt. | Notes |
|---|---|---|---|---|---|
| Abdulai-2018 | LPG | 200 | 0.42 | 0.42 | 58% did not refill stoves more than once |
| Adrianzen-2013 | ICS | 163 | 0.79 | – | Use of stove without problem vs. problem causing stopped usage |
| Adrianzen-2014 | ICS | 26 | 0.45 | – | Village-level average; reproduces above study |
| Alem-2015 | LPG | 296 | 0.75 | – | Reported use within the last week |
| Alexander-2017 | Ethanol | 162 | 0.83 | – | 83% continue to use ethanol after study period |
| Aung-2016 | ICS | 96 | 0.85 | – | 14/96 dropped out; 60% exclusive, 40% partial |
| Bailis-2020 | Gasifier | 83 | 0.67 | 0.93 | SUMs-based; alt from surveys |
| Barstow-2014 | ICS | 1479 | 0.90 | 0.90 | Intervention study, adoption tracked |
| Bensch-2015a | ICS | 377 | 0.89 | – | 15% and 1% in two villages do not use ICS |
| Bensch-2015b | ICS | 1000 | 0.49 | 0.99 | – |
| Berkouwer-2023 | Charcoal | 517 | 0.98 | – | 508/517 still had stove one year later |
| Betina-2022 | ICS | 134 | 0.89 | – | – |
| Beyene-2015 | ICS | 300 | 0.91 | – | 1-year follow-up |
| Bonan-2021 | ICS | 75 | 0.73 | 0.73 | 55/75 used ICS at least once |
| Burwen-2012 | ICS | 768 | 0.49 | 0.65 | In GKH; unclear non-use classification |
| Checkley-2021 | LPG | 90 | 0.99 | – | LPG + free fuel |

**Table S4:** Adoption rates from the academic literature. *(continued)*

| Author-Year | Stove | $N$ | Adopt. | Alt. | Notes |
|---|---|---|---|---|---|
| Christiansen-2012 | Biogas | 610 | 0.93 | – | 93% use for cooking |
| Clark-2017 | Gasifier | 89 | 0.92 | – | 5–10 months post-adoption |
| Diaz-Vasquez-2020 | ICS | 52 | 0.80 | – | After 9 years; 35% had stove destroyed |
| Dickinson-2019 | ICS | 50 | 0.80 | 0.60 | 3-month mark; 3-year mark |
| Dickinson-2019 | ICS | 50 | 0.59 | 0.20 | 3-month mark; 3-year mark (alt group) |
| Dohoo-2013 | Biogas | 31 | 0.77 | – | 77% say biogas is principal fuel source |
| Fankhouser-2019 | ICS | 77417 | 0.94 | 0.77 | 93.8% self-report; 76.9% observed use |
| Gitau-2021 | Gasifier | 50 | 0.96 | – | 48/50 use at least weekly |
| Gupta-2020 | ICS | 65 | 0.54 | – | 53–54% adoption |
| Hankey-2015 | ICS | 32 | 1.00 | – | No households report 0 use; 1-month rates |
| Hing-2023 | ICS | 120 | 0.77 | 0.77 | Free trial data |
| Hing-2023 | ICS | 69 | 0.21 | 0.21 | Follow-up purchase group; sensor-based |
| Jack-2021 | ICS | 527 | 0.69 | – | 69% of visits used intervention stove |
| Jack-2021 | LPG | 361 | 0.87 | – | 87% of visits used LPG stove |
| Jagger-2017 | ICS | 121 | 0.80 | – | 80% actively using after 6 months |
| Keese-2016 | ICS | 43 | 0.70 | – | 30% were non-adopters |
| Kirby-2019 | ICS | 718 | 0.82 | – | Sample size varies across study periods |
| Kongani-2019 | ICS | 28 | 0.50 | – | 50% of recipients using stoves |
| Lafave-2021 | ICS | 480 | 0.60 | – | 3.5 years; 60% continued using |

**Table S4:** Adoption rates from the academic literature. *(continued)*

| Author-Year | Stove | *N* | Adopt. | Alt. | Notes |
|---|---|---|---|---|---|
| Lohani-2025 | ICS | 55 | 0.22 | – | Participants did not like the stoves; Nepal |
| Lung-2019 | ICS | 464 | 0.93 | – | 92.9% for stoves 4+ years old |
| Matavel-2023 | ICS | 357 | 0.58 | 0.58 | Exclude never adopters; % that did not abandon |
| Medina-2019 | ICS | 257 | 0.63 | – | 37% rely exclusively on three-stone fire |
| Mortimer-2017 | ICS | 1427 | 0.78 | 0.92 | 24 months; alt is 3 months post-intervention |
| Mudombi-2018 | Ethanol | 99 | 0.56 | 0.56 | 44% described as ethanol abandoners |
| Northcross-2014 | Ethanol | 25 | 0.90 | – | Stove used 90% of stove-days |
| Pakravan-2018 | ICS | 390 | 0.85 | – | 2-month follow-up; 85% report primary use |
| Pattanayak-2019 | Various | 358 | 0.70 | – | 70% of owners reported use in past week |
| Pillarisetti-2014 | ICS | 146 | 0.94 | – | 6% reported no cooking with ICS |
| Pine-2011 | ICS | 259 | 0.60 | 0.83 | In GKH; 0.6 or 0.83 usage vs. non-adoption |
| Qu-2025 | Ethanol | 400 | 0.94 | – | 94% reported ethanol as primary stove |
| Ramanathan-2016 | ICS | 456 | 0.73 | – | 17 months; 26–29% at 0 daily cooking |
| Romieu-2009 | ICS | 283 | 0.50 | – | 50% classified as primarily using Patsari |
| Rosa-2014 | ICS | 566 | 0.49 | 0.93 | – |
| RuizMercado-2013 | ICS | 80 | 0.90 | 0.95 | In GKH |
| RuizMercado-2015 | ICS | 100 | 0.90 | – | 10% of homes don't use chimney stove |

**Table S4:** Adoption rates from the academic literature. *(continued)*

| Author-Year | Stove | $N$ | Adopt. | Alt. | Notes |
|---|---|---|---|---|---|
| Schillman-2019 | ICS | 257 | 0.80 | 0.80 | Eyeballed at 80% after 2 years |
| Thomas-2013 | ICS | 118 | 0.73 | – | 73.2% sensor-based; 90.5% self-report |
| Usmani-2017 | ICS | 45 | 0.96 | – | All but two adopted |
| Williams-2023 | LPG | 1590 | 0.99 | – | LPG + free fuel |
| Williams-2023b | LPG | 83 | 1.00 | – | All purchased LPG refill within a year |
| Wilson-2016 | ICS | 122 | 0.71 | 0.79 | 71% use stove >10% of days |
| Wolf-2017 | ICS | 1033 | 0.87 | 0.95 | Primary + secondary = 95% for alt |
| Young-2023 | ICS | 230 | 0.98 | – | 98% uptake based on self-report |

**Table S5:** Usage rates drawn from the academic literature used in this study. Usage is defined as the fraction of cooking events performed on the project stove, conditional on adoption.

| Author-Year | Stove | $N$ | Usage | Alt. | Notes |
|---|---|---|---|---|---|
| Barstow-2014 | ICS | 1479 | 0.71 | – | 71.2% of cooking events |
| Bensch-2015b | ICS | 1000 | 0.69 | – | Ratio of ICS uses to total stove applications |
| Burwen-2012 | ICS | 768 | 0.22 | – | SUMs: improved/(improved+traditional) |
| Dohoo-2013 | Biogas | 31 | 0.40 | – | Minutes with biogas exposure |
| Hankey-2015 | ICS | 32 | 0.58 | – | 210 min ICS / (210 + 150 traditional) |
| Jagoe-2020 | ICS | 55 | 0.31 | – | 30% usage; adoption appears 100% |
| Kumar-2022 | LPG | 58 | 0.45 | – | Viable use estimate |
| Lafave-2021 | ICS | 480 | 0.89 | – | 3.5 years; combined adoption/usage measure |
| Lozier-2016 | ICS | 45 | 0.48 | – | Weighted average of cooking events with ICS |
| Northcross-2014 | Ethanol | 25 | 0.90 | – | Stove used 90% of stove-days |
| Piedrahita-2016 | ICS | 50 | 0.62 | – | Gyapa/Gyapa % of total cooking |
| Piedrahita-2016 | ICS | 50 | 0.59 | – | Gyapa/Phillips |
| Piedrahita-2016 | ICS | 50 | 0.32 | – | Phillips/Phillips |
| Pillarisetti-2014 | ICS | 146 | 0.25 | – | Minutes cooking ICS / (ICS + traditional) |
| Qu-2025 | Ethanol | 400 | 0.23 | – | 40 min bioethanol / 177 min total |
| RuizMercado-2015 | ICS | 100 | 0.53 | – | Sample-weighted average of hours |
| Saleh-2022 | ICS | 18 | 0.95 | – | High use; small sample |
| Simons-2017 | ICS | 103 | 0.32 | – | Envirofit usage / total stove usage |

**Table S5:** Usage rates from the academic literature. *(continued)*

| Author-Year | Stove | $N$ | Usage | Alt. | Notes |
|---|---|---|---|---|---|
| Williams-2023b | LPG | 83 | 0.63 | 0.77 | Minutes-based; 0.77 events-based |
| Paulsen-2019 | ICS | 15 | 0.89 | 0.89 | 89% of cooking time; 93% of cooking events |

# S3 Understanding fuel consumption adjustments

There is no replicable procedure for understanding the fuel consumption adjustments made by GKH. Changes can be inferred, with some irregularity, by comparing two Excel files in the replication archive:

- 'Raw' fuel consumption was obtained from `9_27_23_python_inputs_project_recreation_gillwie`
- 'Adjusted' fuel consumption was obtained from `9_27_23_python_inputs_charc_firewood_baselin`

In an Excel file in the replication archive, we found the following table which we reproduce unaltered.

**Table S6:** Fuel adjustments made by GKH, with reported justifications.

| Protocol ID | Adjustment Explanation |
|---|---|
| GS10974 | This project has a low baseline; therefore, we adjusted the baseline up and then we utilized the stove's efficiency to find the project consumption from subtracting baseline savings (from the water boil test efficiency). This is the same approach that the protocol implements. |
| VCS1216 | This project has a high baseline; therefore, we adjusted the baseline down and then we utilized the stove's efficiency to find the project consumption from subtracting baseline savings. |
| GS2094 | This project has a high baseline; therefore, we adjusted the baseline down and then we utilized the stove's efficiency to find the project consumption from subtracting baseline savings. |
| VCS1719 | This project has a low project consumption; therefore, we adjusted the project consumption up to be within the range. |
| VCS1721 | This project has a high baseline; therefore, we adjusted the baseline down and then we utilized the stove's efficiency to find the project consumption from subtracting baseline savings. |

**Table S6:** Fuel adjustments made by GKH, with reported justifications. *(continued)*

| Protocol ID | Adjustment Explanation |
|---|---|
| GS7312 | In the 2020 crediting period, the project has both a high baseline and a low project consumption. Therefore, we both adjust the baseline down and the project consumption up to be within the 2–4 MJ/capita/day range. In the 2021 crediting period, the project has a low project consumption. When we adjust it up to 2 MJ/capita/day, it is larger than the reported baseline. Therefore, we adjust the project consumption up, and then add the original differential that the project reported to that adjusted project consumption to obtain the baseline consumption. |
| GS500 | This project has a low baseline; therefore, we adjust the baseline up to within the range. |
| GS10884 | This project has a low project consumption; therefore, we adjust the project consumption up to within the range. |
| GS447 | This project frames it as biomass savings and combined domestic and commercial values to obtain that biomass saved. We do not adjust commercial consumption and we referred back to their Excel to ensure that their kg/capita/day was within the range of ∼2–4 MJ/capita/day. Therefore, no adjustment was made. |
| GS2564 | Not adjusted; the project's baseline and project includes multiple fuels and in total does not exceed 4 MJ/capita/day. |
| GS7438 | This project has a high baseline and a low project consumption value; therefore, we adjust the baseline down and the project consumption value up to stay in the range. For charcoal, the project has a low project consumption. When we adjust it up to 2 MJ/capita/day, it is larger than the reported baseline. Therefore, we adjust the project consumption up, and then add the original differential that the project reported to that adjusted project consumption to obtain the baseline consumption. |
| GS913 | This project has a high baseline and a low project consumption value; therefore, we adjust the baseline up and the project consumption value up to stay in the range. |

**Table S6:** Fuel adjustments made by GKH, with reported justifications. *(continued)*

| Protocol ID | Adjustment Explanation |
|---|---|
| GS6212 | This project has a high baseline; therefore, we adjusted the baseline down and then we utilized the stove's efficiency to find the project consumption from subtracting baseline savings. |
| GS2758 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS3112 | The project has a low project consumption. When we adjust it up to 2 MJ/capita/day, it is larger than the reported baseline. Therefore, we adjust the project consumption up, and then add the original differential that the project reported to that adjusted project consumption to obtain the baseline consumption. |
| GS5642 | For the first crediting period, the project has a low project consumption value; therefore, we adjust this value up. For the second crediting period, we adjust the firewood down to keep the 2–4 MJ/capita/day total in the project scenario. |
| GS1060 | The project has a low project consumption. When we adjust it up to 2 MJ/capita/day, it is larger than the reported baseline. Therefore, we adjust the project consumption up, and then add the original differential that the project reported to that adjusted project consumption to obtain the baseline consumption. |
| GS2744 | Not adjusted. |
| GS1094 | This project has a high baseline; therefore, we adjusted the baseline down and then we utilized the stove's efficiency to find the project consumption from subtracting baseline savings. |
| GS4291 | This project has a high baseline; therefore, we adjusted the baseline down and then we utilized the stove's efficiency to find the project consumption from subtracting baseline savings. |
| GS6604 | The project has a low project consumption. So we adjust the project consumption up to be within the range. |
| GS1267 | This project has a high baseline and a low project consumption value; therefore, we adjust the baseline up and the project consumption value up to stay in the range. |

**Table S6:** Fuel adjustments made by GKH, with reported justifications. *(continued)*

| Protocol ID | Adjustment Explanation |
|---|---|
| GS2439 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS2445 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS7578 | Not adjusted. |
| GS2513 | Not adjusted. |
| GS4677 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS2441 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS5003 | Scaled back project charcoal as total baseline and project consumption was over 4 MJ/capita/day across firewood and charcoal. Therefore, we took a combination of firewood and charcoal based on the KPT ratio that would have the combination stay under the range, then subtracted the charcoal savings from that new baseline value for the project scenario. |
| GS6129 | This project has a high baseline and a low project consumption value; therefore, we adjust the baseline up and the project consumption value up to stay in the range. |
| GS407 | The project has a low project consumption. We thus adjust it up to 2 MJ/capita/day. We do not adjust the commercial stoves. |
| GS11509 | This project has a low project consumption; therefore, we adjust the project consumption up to within the range. |
| GS11352 | This project has a low project consumption; therefore, we adjust the project consumption up to within the range. |
| GS11507 | This project has a low project consumption; therefore, we adjust the project consumption up to within the range. |
| GS1146 | In the exclusive LPG scenario, the project has a low project consumption value, so we adjust it up to stay within the range. The other scenarios are already within the range. We do not adjust the commercial scenario. |

**Table S6:** Fuel adjustments made by GKH, with reported justifications. *(continued)*

| Protocol ID | Adjustment Explanation |
|---|---|
| GS 11330 | This project has a low project consumption; therefore, we adjust the project consumption up to within the range. |
| GS 3071 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS 10777 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS 10886 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS 5107 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS 11195 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS 2077 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS 411 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS 10914 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS 10781 | This project has a high baseline; therefore, we adjusted the baseline down. |
| GS 5660 | This project has a high baseline; therefore, we adjusted the baseline down. |

Some projects that were noted as not having been changed appear to have different fuel consumption values between what we interpreted as the ‘raw’ fuel consumption and the ‘adjusted’ fuel consumption.

## S3.1 Assessment of GKH’s fuel adjustment approach

Several features of GKH’s fuel adjustment methodology merit careful consideration.

**No replicable algorithm.** GKH state that they "confine fuel consumption values to a reasonable literature-derived range of 2–4 MJ per capita per day." However, the replication archive contains no code, formula, or intermediate calculation implementing this procedure. The adjustment is documented only as two Excel files—one with raw PDD values, one with adjusted values—and 46 free-text project-by-project explanations (Table S6). We were unable to reconstruct the transformation from raw to adjusted values using any systematic rule. The procedure is therefore not independently reproducible.

**Evidence of an energy-delivered target.** The 2–4 MJ/capita/day range stated by GKH refers to energy *delivered to the pot*, not raw fuel energy. For the 14 projects with non-zero stove efficiency data in the replication archive, we find that GKH's adjusted baselines consistently converge on approximately 4.0 MJ delivered per capita per day (mean scale error 2.8%). For the remaining projects with efficiency recorded as zero, an implied efficiency of approximately 0.10 achieves the same delivered-energy target. However, to our knowledge, stove efficiency is never referenced in GKH's analysis code—rather it appears to be dead code that is loaded but not used in any calculation. The analysis computes fuel energy simply as kg $\times$ NCV (not as delivered energy via stove efficiency). The adjustments thus appear to have been performed in a delivered-energy framework external to the analysis pipeline. Project-side adjustments cannot be replicated by any systematic rule we tested (best method: 36.6% mean error across four candidate algorithms).

**Systematic asymmetry in the direction of adjustments.** Comparing the two Excel files across all 151 monitoring periods reveals that 139 rows (92%) had at least one fuel value changed. The adjustments are systematically asymmetric:

- Firewood baselines were changed in 113 rows: 103 were *decreased* and 10 were *increased*. The mean firewood baseline fell from 13.7 kg/stove/day (raw) to 8.1 kg/stove/day (adjusted), a reduction of 41%.
- Firewood project values were changed in 95 rows: 53 were *decreased* and 42 were *increased*. The mean firewood project consumption fell from 5.6 to 4.8 kg/stove/day, a reduction of 16%.
- Mean implied firewood savings fell from 8.1 to 3.3 kg/stove/day—a compression of 59%.

This pattern is consistent with a procedure that primarily constrains baseline fuel consumption downward while leaving project consumption relatively unchanged, systematically compressing apparent fuel savings.

**Multiple adjustment strategies without stated selection criteria.** The 46 project-level explanations in Table S6 reveal at least six distinct adjustment strategies: (1) reduce high baseline only; (2) reduce high baseline and infer project from water boil test (WBT) stove efficiency; (3) increase low project consumption only; (4) adjust both baseline and project simultaneously; (5) invert the baseline-project relationship when raising project consumption above the reported baseline; and (6) balance across fuel types using kitchen performance test (KPT) ratios. No rule is stated for when each strategy applies, and some explanations appear internally inconsistent (e.g., GS913 and GS1267 state "we adjust the baseline *up*" for a project described as having a "high baseline").

**Species-specific corrections are undisclosed.** Beyond the stated 2–4 MJ/capita/day bounds, the adjusted values also reflect fuel-species corrections that are not described in GKH's paper or supplement. These corrections appear to account for differences in energy content across wood species and charcoal forms. The corrections are asymmetric: baselines (which skew toward hardwood in the sample) are reduced more aggressively than project values. This additional layer of adjustment is documented only implicitly through the difference between the two Excel files.

**Independent capping destroys measured stove efficiency.** Perhaps most importantly, GKH's approach clamps baseline and project fuel consumption independently against the 2–4 MJ/capita/day range. Consider a project that measures a stove reducing firewood use from 10 kg/day (baseline) to 3 kg/day (project), implying 70% savings. If the baseline exceeds 4 MJ/capita/day and is clamped to an adjusted value of, say, 5 kg/day, while the project value of 3 kg/day remains unchanged, implied savings fall from 70% to 40%. The savings ratio $r = 1 - W_{\text{project}}/W_{\text{baseline}}$ reflects actual measured stove performance; independent capping replaces this measurement with an artifact of the bounding procedure. This concern motivates our ratio-preserving alternatives (Models 8–9 and 17–20), which anchor one side of the fuel equation and infer the other from the measured efficiency ratio.

## S3.2 Ratio-preserving fuel consumption bounds (this study)

GKH's fuel adjustment procedure is not fully reproducible and involves ad hoc decisions for individual projects. In this study, we propose two systematic, ratio-preserving alternatives that bound fuel consumption within the 2–4 MJ/capita/day range while preserving the proportional fuel savings implied by the original project data.

Let $r = (W_{\text{baseline}} - W_{\text{project}})/W_{\text{baseline}}$ denote the fractional fuel reduction reported by the project. Our two approaches are:

- **Model 8 (V1, cap baseline):** If baseline fuel consumption exceeds 4 MJ/capita/day, set $W^{V1}_{\text{baseline}} = \min(W^{\text{adj}}_{\text{baseline}}, 4)$ and infer $W^{V1}_{\text{project}} = W^{V1}_{\text{baseline}} \times (1 - r)$. If project consumption falls below 2 MJ/capita/day, set $W^{V1}_{\text{project}} = \max(W^{\text{adj}}_{\text{project}}, 2)$ and infer baseline from $r$.
- **Model 9 (V2, cap project):** If project fuel consumption falls below 2 MJ/capita/day, set $W^{V2}_{\text{project}} = \max(W^{\text{adj}}_{\text{project}}, 2)$ and infer $W^{V2}_{\text{baseline}} = W^{V2}_{\text{project}}/(1 - r)$. If baseline exceeds 4 MJ/capita/day, cap and infer project from $r$.

Crucially, baseline and project fuel consumption are *not* clamped independently—doing so would destroy the proportional relationship between baseline and project consumption that reflects actual stove efficiency.

For charcoal fuel consumption, we use the raw PDD values directly without applying the 2–4 MJ/capita/day cap, as GKH's species correction for charcoal is already aggressive.

## S3.3 Projects excluded from ratio-preserving fuel adjustments

We identify 17 projects (40 monitoring period rows) where fuel consumption values in the raw PDD file do not represent standard fuel consumption, making the raw efficiency ratio meaningless for our ratio-preserving adjustments. For these projects, V1 and V2 fall back to GKH-adjusted values (preserving GKH's original treatment). CLEAR treatment is project-specific, as detailed in Table S7.

These 17 projects fall into five categories:

- **Group A** (4 IDs, 7 periods): GKH made no change to fuel consumption values (raw = adjusted). CLEAR uses raw PDD values, which are identical to GKH-adjusted.
- **Group B** (4 IDs, 5 periods): Ethanol baseline projects. The raw firewood baselines represent genuine pre-ethanol cooking fuel consumption. GKH reduced these baselines through their energy-delivered adjustment procedure and in some cases reclassified fuel types (e.g., adding charcoal). CLEAR uses the raw PDD values, which represent actual consumption, subject to the CLEAR plausibility cap.
- **Group C** (4 IDs, 21 periods): Fuel-type reclassification. The raw PDD file records fuel under the firewood column, but GKH classifies these projects as primary charcoal

(`prc_ch = 1`). GKH converted the values to charcoal equivalents. Using raw firewood values would produce zero emissions (firewood is zeroed by `prc_fw = 0`) and infinite overcrediting. CLEAR must use GKH-adjusted charcoal values.

- **Group D** (3 IDs, 3 periods): GS Metered methodology projects. The raw PDD file contains all zeros for fuel consumption. GKH constructed charcoal-equivalent values from pellet conversion factors. CLEAR must use GKH-adjusted values, as no raw fuel data exist.
- **Group E** (2 IDs, 4 periods): Special encoding. Raw values do not represent fuel consumption: GS447's baseline represents biomass saved (not consumed), and GS7438 embeds firewood-charcoal conversion factors in the emission factor rather than in fuel quantities. CLEAR must use GKH-adjusted values.

**Table S7:** Projects excluded from ratio-preserving fuel adjustments. For each project, we document the reason for exclusion, what GKH did, and our treatment for V1/V2 (ratio-preserving) and CLEAR (raw PDD-based) fuel adjustments.

| Project ID | Group | Periods | Reason for exclusion | GKH action | V1/V2 | CLEAR |
|---|---|---|---|---|---|---|
| GS500 | A | 1 | Suppressed demand baseline; LPG project | No change | GKH-adj | Raw PDD |
| GS2564 | A | 1 | FW-CH conversion in emission factor | No change | GKH-adj | Raw PDD |
| GS1146 | A | 4 | GS TPDDTEC LPG project; multiple stacking scenarios | No change | GKH-adj | Raw PDD |
| GS 11330 | A | 1 | GS LPG project | No change | GKH-adj | Raw PDD |
| GS10884 | B | 2 | Ethanol; raw FW baseline is real | Reduced FW baseline | GKH-adj | Raw PDD |
| GS7578 | B | 1 | Ethanol; raw FW baseline is real (11.1 kg) | Reduced to 4.0 + added CH | GKH-adj | Raw PDD |

Table S7: Projects excluded from ratio-preserving fuel adjustments. *(continued)*

| Project ID | Group | Periods | Reason for exclusion | GKH action | V1/V2 | CLEAR |
|---|---|---|---|---|---|---|
| GS2513 | B | 1 | Ethanol; raw FW baseline is real (16.8 kg) | Reduced to 6.6 + added CH | GKH-adj | Raw PDD |
| GS4677 | B | 1 | Ethanol; raw FW baseline is real (13.2 kg) | Reduced to 12.0 | GKH-adj | Raw PDD |
| GS2094 | C | 12 | "Charcoal treated as FW" in PDD | FW→CH reclassification | GKH-adj | GKH-adj |
| GS1060 | C | 6 | Pure CH project; raw has FW only | FW→CH reclassification | GKH-adj | GKH-adj |
| GS5642 | C | 2 | FW in raw but `prc_ch=1` | FW→CH reclassification | GKH-adj | GKH-adj |
| GS 10914 | C | 1 | FW in raw but `prc_ch=1` | FW→CH reclassification | GKH-adj | GKH-adj |
| GS11509 | D | 1 | GS Metered; raw = 0 | Constructed CH from pellets | GKH-adj | GKH-adj |
| GS11352 | D | 1 | GS Metered; raw = 0 | Constructed CH from pellets | GKH-adj | GKH-adj |
| GS11507 | D | 1 | GS Metered; raw = 0 | Constructed FW+CH from pellets | GKH-adj | GKH-adj |

**Table S7:** Projects excluded from ratio-preserving fuel adjustments. *(continued)*

| Project ID | Group | Periods | Reason for exclusion | GKH action | V1/V2 | CLEAR |
|---|---|---|---|---|---|---|
| GS447 | E | 2 | Baseline = biomass saved | Reduced CH baseline | GKH-adj | GKH-adj |
| GS7438 | E | 2 | FW-CH conversion in EF | Adjusted both fuels | GKH-adj | GKH-adj |

## S3.4 CLEAR fuel adjustments

We additionally implement fuel adjustments using the CLEAR methodology (August 2025), which applies plausibility caps based on raw PDD values rather than GKH-adjusted values. The CLEAR caps are 2.0 tonnes/person/year for primary firewood and 0.40 tonnes/person/year for primary charcoal. Both CLEAR V1 (cap baseline) and CLEAR V2 (cap project) use ratio-preserving inference for the uncapped side, and charcoal caps are applied with the same ratio-preserving logic as firewood.

For excluded projects, CLEAR treatment is project-specific (Table S7): Groups A and B use raw PDD values (genuine consumption or unchanged by GKH), while Groups C, D, and E use GKH-adjusted values (where raw data are unusable due to fuel-type reclassification, missing data, or special encoding).

# S4 Cookstove projects included in the study

Our analysis includes the same 51 improved cookstove carbon credit projects analysed by GKH, spanning multiple voluntary carbon registries (Gold Standard, Verra/VCS) and crediting methodologies (CDM AMS II G, CDM AMS I E, GS Simplified, GS TPDDTEC, GS Metered). Projects cover 151 monitoring periods across countries in Sub-Saharan Africa, South Asia, Southeast Asia, and Latin America. Table S8 provides descriptions of all 51 projects.

**Table S8:** Cookstove projects included in the study and their descriptions.

| Project ID | Project Name | Developer | Registry | VPA/PoA | Methodology | Country/Context | Implementation | Pre-Project Fuel |
|---|---|---|---|---|---|---|---|---|
| GS 447 | Improved Cookstoves for Social Impact in Ugandan Communities | Impact carbon | GOLD | Standalone | GS TPDDTEC v2 | Uganda | Retail stove sales | Charcoal, wood |
| GS 500 | Darfur Efficient Cook-stove Project | Carbon clear | GOLD | Standalone | AMS-II.G. v5 | El Fashir, Sudan | LPG distribution | Charcoal, wood |
| GS 2564 | Expanding access to LPG in Haiti through microfinance | Entrepreneurs du Monde | GOLD | Standalone | AMS-II.G. v3 | Port au Prince, Haiti | Microfinance | Charcoal |
| GS 2094 | Man and Man Enterprise ICS Programme | Man and Man Enterprise | GOLD | PoA 1385 | AMS-II.G. v3 | Ghana (urban) | Direct/vendor sales | Charcoal |
| VCS 1719 | Improved Cookstoves for Malawi and Mozambique | C-Quest Capital | VCS | Standalone | AMS-II.G. v3 | Malawi | Direct distribution | Firewood |
| VCS 1721 | ONIL Stoves Guatemala Uspantan | C-Quest Capital | VCS | Grouped | AMS-I.E. v9 | Guatemala | Manufacture/distribution | Firewood, open fires |
| VCS 1216 | Distribution of ONIL Stoves – Mexico | C-Quest Capital | VCS | Grouped | AMS-I.E. v9 | Mexico | Manufacture/distribution | Firewood |

Table S8: Cookstove projects included in the study. *(continued)*

| Project ID | Project Name | Developer | Registry | VPA/PoA | Methodology | Country/Context | Implementation | Pre-Project Fuel |
|---|---|---|---|---|---|---|---|---|
| GS 10974 | Improved Cooking Stoves in Bangladesh | Bangladesh Bondhu Foundation | GOLD | PoA 10833 | GS TPDDTEC v3.1 | Bangladesh | Stove construction | Firewood |
| GS 10884 | KOKO Kenya – Ethanol Cookstoves | KOKO Network Limited | GOLD | PoA 10884 | GS Simplified v2 | Kenya | Ethanol stove distribution | Charcoal, firewood |
| GS 7312 | Promoting Improved Cooking in Nigeria | Toyola Energy | GOLD | Standalone | GS TPDDTEC v2 | Nigeria | Local artisan construction | Solid fuel, open fires |
| GS 7438 | Improved Cookstove Project in Uganda | South Pole Ltd | GOLD | Standalone | GS TPDDTEC v2 | Uganda | Partner distribution | Woody biomass |
| GS 1060 | Improved Cook Stoves for Rwanda | Atmosfair gGmbH | GOLD | PoA 1023 | AMS-II.G. v3 | Rwanda | National dissemination | Firewood/charcoa |
| GS 1094 | WWF Mamize Firewood-Saving Stove I | South Pole Ltd | GOLD | Standalone | AMS-II.G. v3 | Sichuan, China | Free deployment | Firewood |
| GS 2744 | Local Improved Cookstoves in Bamako | GERES | GOLD | PoA 2486 | AMS-II.G. v5 | Mali (Bamako) | Local production/retail | Charcoal, firewood |

**Table S8:** Cookstove projects included in the study. *(continued)*

| Project ID | Project Name | Developer | Registry | VPA/PoA | Methodology | Country/Context | Implementation | Pre-Project Fuel |
|---|---|---|---|---|---|---|---|---|
| GS 4291 | Breathing Space ICS – India (Envirofit) | Envirofit International | GOLD | PoA 916 | AMS-II.G. v3 | India | Commercial distribution | Traditional chulhas |
| GS 6604 | Energy efficiency project (Uganda) | Pacific Engineering | GOLD | Standalone | AMS-II.G. v9 | Uganda | Distribution | Firewood, open fires |
| GS 1267 | Improved Kitchen Regimes: Bugesera, Rwanda | CO2balance UK | GOLD | PoA 1247 | GS TPDDTEC v1 | Rwanda (Bugesera) | Subsidized installation | Firewood, open fires |
| GS 2439 | Utsil Naj VPA2 (Guatemala) | MICROSOL SAS | GOLD | PoA 1377 | GS TPDDTEC v1 | Guatemala | Local partner distribution | Firewood, charcoal |
| GS 2441 | Utsil Naj VPA4 (Mexico) | MICROSOL SAS | GOLD | PoA 1377 | GS TPDDTEC v1 | Mexico | Local partner distribution | Firewood |
| GS 5003 | Bamako Clean Cookstoves – Sahel | Swiss Carbon Value | GOLD | Standalone | GS TPDDTEC v2 | Mali | Commission agent retail | Charcoal, firewood |
| GS 2445 | African Biomass Energy Conservation – Malawi | Hestian Innovation | GOLD | PoA 1265 | GS TPDDTEC v1 | Malawi | National dissemination | Firewood, charcoal |

**Table S8:** Cookstove projects included in the study. *(continued)*

| Project ID | Project Name | Developer | Registry | VPA/PoA | Methodology | Country/Context | Implementation | Pre-Project Fuel |
|---|---|---|---|---|---|---|---|---|
| GS 3112 | Bondhu Chula ICS in Bangladesh | Bangladesh Bondhu Foundation | GOLD | PoA 3112 | GS Simplified v1 | Bangladesh | Subsidized installation | Solid biomass |
| GS 2456 | Efficient cookstoves in Burkina Faso | tiipaalga / Livelihoods Fund | GOLD | PoA (GS1340) | GS Simplified v1 | Burkina Faso | Local construction/dissemination | Firewood/charcoa |
| GS 2513 | CleanStar Mozambique – Ethanol Cookstove | CleanStar Mozambique | GOLD | Standalone | AMS-I.E. | Mozambique (Maputo) | Ethanol stove + fuel sales | Charcoal |
| GS 2896 | Fuel Efficient Stoves for North Darfur Women | Haggar Group / WDAN | GOLD | Standalone | GS Simplified | Sudan (North Darfur) | Community distribution | Firewood/charcoa |
| GS 3018 | Improved Cook Stove with Carbon Finance, Nepal | SNV / CRT/N | GOLD | Micro-scale | GS Simplified | Nepal | Local manufacture/install | Firewood |
| GS 3422 | ICS in Pastoral Communities, Southern Ethiopia | Carbon Sink Group | GOLD | Standalone | GS Simplified v1 | Ethiopia | ICS production/dissemination | Firewood |
| GS 4677 | Project Gaia Stove PoA – Ethiopia | Project Gaia Inc. | GOLD | PoA 10340 | AMS-I.E. | Ethiopia | Ethanol stove distribution | Firewood/charcoa |

**Table S8:** Cookstove projects included in the study. *(continued)*

| Project ID | Project Name | Developer | Registry | VPA/PoA | Methodology | Country/Context | Implementation | Pre-Project Fuel |
|---|---|---|---|---|---|---|---|---|
| GS 6129 | Myanmar Stoves Campaign – VPA 007 | QK TS Pvt. Ltd. | GOLD | PoA 1729 | GS Simplified v1 | Myanmar | Retail stove sales | Firewood |
| GS 11352 | Kenya Biomass Gasification (EcoSafi) | Better Cooking Company | GOLD | Standalone | GS Metered v1+ | Kenya | Commercial sales + metered | Charcoal/wood |
| GS 11507 | Advanced Biomass Cooking – Rwanda (BioMassters) | FairClimateFund | GOLD | PoA (GS11506) | GS Metered | Rwanda | Gasifier stove + pellets | Charcoal, firewood |
| GS 11509 | Clean Cooking Biomass Gasification – Zambia | Emerging Cooking Solutions | GOLD | PoA/Grouped | GS Metered | Zambia | Metered pellet gasifier | Charcoal, firewood |
| GS 407 | Gyapa Cook Stoves Project in Ghana | Relief International | GOLD | Standalone | GS TPDDTEC v2 | Ghana | Commercial retail | Charcoal |
| GS 913 | Efficient Wood Fuel Stove-Sets, Lesotho | Atmosfair gGmbH | GOLD | Standalone | AMS-II.G. v3 | Lesotho | Subsidized sales | Firewood |
| GS 6212 | Promoting Clean Cooking – Nepal | Value Network Venture | GOLD | Standalone | AMS-II.G. v9 | Nepal (Terai) | Free distribution | Firewood |

**Table S8:** Cookstove projects included in the study. *(continued)*

| Project ID | Project Name | Developer | Registry | VPA/PoA | Methodology | Country/Context | Implementation | Pre-Project Fuel |
|---|---|---|---|---|---|---|---|---|
| GS 2758 | Proyecto Mirador – Honduras | Proyecto Mirador | GOLD | PoA 1988 | GS TPDDTEC v2 | Honduras | Local installation | Fogón (open biomass) |
| GS 5642 | Burn Stoves Project in Kenya | ECOA Climate Capital | GOLD | Standalone | GS TPDDTEC v2 | Kenya | Market-based distribution | Firewood, charcoal |
| GS 1146 | Expanding LPG Access in Burkina Faso | Entrepreneurs du Monde | GOLD | PoA | GS TPDDTEC v3.1 | Burkina Faso | Microfranchised distribution | Wood, charcoal |
| GS 11330 | Circle Gas LPG Smart Meter Program | Climate Impact Partners | GOLD | PoA | GS TPDDTEC v3.1 | Kenya | Metered LPG distribution | Wood, charcoal |
| GS 7578 | Garner Mozambique – Bioethanol CPA1 | Garner Advisors LLC | GOLD | PoA 7577 | AMS-I.E. v10 | Mozambique (Maputo) | Ethanol stove distribution | Charcoal, wood |
| GS 1028 | Efficient Cookstoves in Bahia II | Instituto Perene | GOLD | Standalone | GS Simplified v1 | Brazil (Bahia) | Local stove construction | Wood |
| GS 3071 | Micro Energy PoA – VPA 2 West Cameroon | QK TS Pvt. Ltd. | GOLD | PoA 1366 | GS TPDDTEC v1 | Cameroon | Local stove construction | Three-stone fires |

**Table S8:** Cookstove projects included in the study. *(continued)*

| Project ID | Project Name | Developer | Registry | VPA/PoA | Methodology | Country/Context | Implementation | Pre-Project Fuel |
|---|---|---|---|---|---|---|---|---|
| GS 10777 | Efficient Cookstoves – Urban Maputo | Carbonsink Group | GOLD | PoA 5658 | GS TPDDTEC v3.1 | Mozambique (Maputo) | Direct sales | Charcoal |
| GS 10886 | African ICS Programme – Zambia | Commonland B.V. | GOLD | PoA 10874 | GS TPDDTEC v3.1 | Zambia (Simalaha) | Commercial ICS distribution | Traditional biomass |
| GS 5107 | Qori Q'oncha ICS – Peru (VPA 5) | Livelihoods Fund | GOLD | PoA 1005 | GS TPDDTEC v2 | Peru (Huancavelica) | Installation + education | Wood |
| GS 11195 | BioLite HomeStove in Kenya (CPA 041) | BioLite, Inc. | GOLD | PoA 11191 | AMS-II.G. v3 | Kenya | Retail distribution | Biomass |
| VCS 2077 | Tuik Ruch Lew ICS – Guatemala | Asociación Tuik Ruch Lew | VCS | Standalone | AMS-II.G. v11.1 | Guatemala (Lake Atitlán) | NGO distribution/training | Open fires |
| GS 411 | Efficient Fuel Wood Stoves for Nigeria | Atmosfair gGmbH | GOLD | Standalone | AMS-II.G. v1 | Nigeria (Savannah Zone) | Subsidized sales | Wood fires |
| GS 10914 | UpEnergy ICS Programme – Uganda | UpEnergy Group | GOLD | PoA 10898 | AMS-II.G. v12 | Uganda | Marketing + distribution | Biomass |
| GS 10781 | ICS in Burkina Faso – VPA-17 (Nahouri) | Tipaalga | GOLD | PoA 1340 | GS Simplified v1 | Burkina Faso (Nahouri) | Local women-led construction | Open fires |

**Table S8:** Cookstove projects included in the study. *(continued)*

| Project ID | Project Name | Developer | Registry | VPA/PoA | Methodology | Country/Context | Implementation | Pre-Project Fuel |
|---|---|---|---|---|---|---|---|---|
| GS 5660 | Myanmar Stoves Campaign – VPA 004 | QK TS Pvt. Ltd. | GOLD | PoA 1729 | GS Simplified v1 | Myanmar | Retail sales | Firewood |

# S5 Supplementary methods

This section details the analytical methods used throughout the study, including the Monte Carlo simulation design, aggregation procedures, rebound correction methodology, and confidence interval construction.

## S5.1 Monte Carlo simulation design

All models use $N = 10{,}000$ Monte Carlo draws with `set.seed(4)` to match GKH's original simulation design. For each draw $j \in \{1, \ldots, 10{,}000\}$ and each monitoring period $i \in \{1, \ldots, 151\}$, we sample behavioural parameters from their respective distributions:

- **Adoption:** $a_{ij} \sim \text{Logit-Normal}(\hat{\mu}_a, \hat{\tau}_a^2)$, where $\hat{\mu}_a$ and $\hat{\tau}_a^2$ are estimated via random-effects meta-analysis (REML) on logit-transformed proportions from 60 studies.
- **Usage:** $u_{ij} \sim \text{Logit-Normal}(\hat{\mu}_u, \hat{\tau}_u^2)$, similarly estimated from 20 studies.
- **Stacking:** $s_{ij} \sim \text{Uniform}(0, 0.05)$, reflecting near-zero residual stacking.
- **GKH original distributions (Models 1–2):** Adoption $\sim$ Triangular(0.40, 0.92, 0.58); Usage $\sim$ Triangular(0.16, 0.85, 0.52); Stacking $\sim$ Triangular(0.193, 0.99, 0.673).

For each draw, estimated true emission reductions are computed as:

$$\text{VERs}_{ij}^{\text{agw}} = \text{VERs}_i^{\text{issued}} \times \frac{a_{ij} \times u_{ij} \times (1 - s_{ij}) \times \Delta_{\text{fuel},i}^{\text{model}} \times \text{fNRB}_i^{\text{model}}}{\Delta_{\text{fuel},i}^{\text{PDD}} \times \text{fNRB}_i^{\text{PDD}}} \tag{S1}$$

where $\Delta_{\text{fuel}}$ denotes net fuel savings and the ratio adjusts credits for parameter differences between the model and project design document (PDD) assumptions.

## S5.2 Rebound correction

GKH apply rebound as a flat percentage discount on credits. We instead apply the rebound effect to energy consumption (MJ) first, then reallocate to fuels proportionally by the project's fuel mix. Specifically, for a rebound rate $\rho$ (22% in Model 3; 10% in Model 5):

1. Compute total energy savings: $\Delta E_i = \sum_f (W_{f,\text{base},i} - W_{f,\text{proj},i}) \times \text{EF}_f$
2. Rebound energy: $E_{\text{rebound},i} = \rho \times \Delta E_i$
3. Allocate rebound to each fuel $f$ proportionally to project fuel share: $W_{f,\text{rebound},i} = E_{\text{rebound},i} \times (W_{f,\text{proj},i} / \sum_f W_{f,\text{proj},i})$
4. Adjusted project fuel: $W_{f,\text{proj},i}^{\text{adj}} = W_{f,\text{proj},i} + W_{f,\text{rebound},i} / \text{EF}_f$

This approach avoids double-counting when fuel compositions differ between baseline and project periods.

## S5.3 Sector-level aggregation

We report three aggregation methods, each answering a slightly different question:

**VER-weighted harmonic mean (primary).** This matches GKH's original method:

$$\mathrm{OC}_{\mathrm{sector}} = \frac{\sum_p \mathrm{VERs}_p}{\sum_p \left(\mathrm{VERs}_p \,/\, \bar{R}_p\right)} \tag{S2}$$

where $\bar{R}_p = \mathrm{E}[\mathrm{VERs}_p/\mathrm{VERs}_p^{\mathrm{agw}}]$ is the mean overcrediting ratio for project $p$ across Monte Carlo draws. This gives more weight to projects with more credits.

**Stove-day-weighted (SDW) mean.** For each draw $j$:

$$R_j^{\mathrm{SDW}} = \frac{\sum_p R_{pj} \times D_p}{\sum_p D_p} \tag{S3}$$

where $D_p$ is total stove-days for project $p$. The reported SDW value is $\mathrm{E}[R_j^{\mathrm{SDW}}]$.

**Ratio-of-sums (ROS) mean.** For each draw $j$:

$$R_j^{\mathrm{ROS}} = \frac{\sum_p \mathrm{VERs}_p}{\sum_p \mathrm{VERs}_{pj}^{\mathrm{agw}}} \tag{S4}$$

Due to Jensen's inequality, these methods yield different point estimates. For Model 1: VER-weighted harmonic mean = 9.24×, SDW = 9.71×, ROS = 7.55×.

## S5.4 Confidence intervals

We construct 95% confidence intervals using quantiles from the Monte Carlo distribution:

$$\mathrm{CI}_{95} = \left[Q_{0.025}(R_1^{\mathrm{SDW}}, \ldots, R_{10000}^{\mathrm{SDW}}),\ Q_{0.975}(R_1^{\mathrm{SDW}}, \ldots, R_{10000}^{\mathrm{SDW}})\right] \tag{S5}$$

These intervals reflect parameter uncertainty (adoption, usage, stacking distributions) propagated through the Monte Carlo simulation. They do not capture model specification uncertainty (e.g., choice of fuel adjustment method or fNRB value).

## S5.5 CLEAR energy consumption caps

The CLEAR methodology (Clean Cooking Alliance, August 2025) specifies maximum plausible energy consumption rates for cookstove projects:

| Fuel type | Cap (t/person/year) | Cap (kg/person/day) |
|---|---:|---:|
| Firewood (primary, >75% of fuel) | 2.0 | 5.48 |
| Charcoal (primary, >75% of fuel) | 0.40 | 1.10 |
| Mixed/other fuels | No cap | – |

Caps are applied per person per day, scaled to per-stove-day using household size (assumed 5 persons). Commercial monitoring periods are exempt from all caps.

# S6 Model specifications and results

We estimate overcrediting under 19 model specifications, each modifying one or more parameters relative to GKH's baseline. All models use 10,000 Monte Carlo draws with `set.seed(4)` to match GKH's simulation design. Confidence intervals are 2.5th–97.5th percentile quantiles from the stove-day-weighted sector ratio distribution.

**Table S9:** Estimated overcrediting under alternative assumptions. "Sample overcrediting" is the VER-weighted sector-wide ratio; 95% CI from quantile-based Monte Carlo draws. "Project overcrediting" reports the median and interquartile range across 51 projects.

| # | Model description | Category | OC | CI low | CI high | Median | IQR low |
|---|---|---|---|---|---|---|---|
| *Replication and Basic Corrections* | | | | | | | |
| 1 | GKH replication | Baseline | 9.24 | 6.77 | 13.74 | 16.15 | 7.96 |
| 2 | + GS3112 credit correction | Correction | 9.30 | 6.77 | 13.74 | 16.15 | 7.96 |
| 3 | + Rebound correction (22%, energy-based) | Correction | 9.85 | 7.16 | 14.54 | 18.79 | 8.25 |
| 4 | + Stacking partial discount (50%) | Correction | 9.26 | 6.77 | 13.69 | 11.80 | 7.47 |
| 5 | + Lower rebound (10%) | Correction | 8.73 | 6.42 | 12.98 | 10.26 | 7.04 |
| *Behavioural Distribution Updates* | | | | | | | |
| 6 | + Meta-analytic adoption, usage, stacking distributions | Behavioural | 6.72 | 4.85 | 16.50 | 7.27 | 5.06 |
| 7 | + No Hawthorne discount on measured protocols | Behavioural | 5.39 | 3.98 | 13.58 | 6.76 | 4.20 |
| *Fuel Consumption Adjustments* | | | | | | | |
| 8 | + Fuel bounds V1 (cap baseline) | Fuel | 2.71 | 1.95 | 7.40 | 4.97 | 2.88 |
| 9 | + Fuel bounds V2 (cap project) | Fuel | 2.57 | 1.87 | 6.90 | 3.41 | 2.03 |
| *Joint Implementation Corrections* | | | | | | | |
| 10 | Joint Models 2–6 | Joint | 6.26 | 4.50 | 14.91 | 6.77 | 4.71 |
| 11 | Joint Models 2–6 + 7 | Joint | 5.05 | 3.72 | 12.47 | 6.13 | 3.64 |

**Table S9:** Estimated overcrediting under alternative assumptions. *(continued)*

| # | Model description | Category | OC | CI low | CI high | Median | IQR low |
|---|---|---|---|---|---|---|---|
| 12 | Joint Models 2–6 + 7 + 8 (fuel V1) | Combined | 1.87 | 1.44 | 5.06 | 3.70 | 2.35 |
| 13 | Joint Models 2–6 + 7 + 9 (fuel V2) | Combined | 1.79 | 1.37 | 4.80 | 2.87 | 1.67 |
| *fNRB Sensitivity* | | | | | | | |
| 14 | fNRB = 30% (both sides) | Science | 3.59 | 2.63 | 7.71 | 4.35 | 2.44 |
| 15 | max(Bailis, 30%) fNRB (practice gap) | Practice | 8.04 | 5.81 | 12.57 | 8.53 | 4.84 |
| *Combined Best Estimates* | | | | | | | |
| 16 | Joint V1 + max(Bailis, 30%) fNRB | Combined | 1.71 | 1.32 | 3.91 | 2.45 | 1.61 |
| 17 | Joint V2 + max(Bailis, 30%) fNRB | Combined | 1.60 | 1.21 | 3.60 | 1.86 | 1.05 |
| *CLEAR Methodology* | | | | | | | |
| 18 | CLEAR fuel V1 standalone | CLEAR | 3.44 | 2.47 | 5.14 | 7.21 | 4.63 |
| 19 | CLEAR fuel V2 standalone | CLEAR | 3.43 | 2.46 | 5.10 | 7.21 | 4.63 |

## S6.1 Model descriptions

All 19 model specifications are summarized in Table S9. Below we note additional technical details not captured in the table.

**Model 2.** GKH used 517,943 credits for project GS3112 from the PDD, which matched the credit count for a different project (GS6604). The verified issuance from the Verra registry is 312,478 credits.

**Model 3.** GKH apply rebound as a flat 22% discount on credits. We apply rebound to energy (MJ) first, then reallocate to fuels proportionally by project fuel mix—methodologically more appropriate as rebound affects energy consumption, not credits directly.

**Model 7.** For protocols that directly measure stove performance (GS-TPDDTEC, GS-Metered), we scale by adoption only. GKH apply the full $a \times u \times (1 - s)$ discount to all protocols regardless of measurement method.

**Models 8–9.** Ratio-preserving fuel consumption bounds as described in Section S3.2. The 17 projects excluded from ratio-preserving adjustments (Section S3.3) fall back to GKH-adjusted values.

**Models 18–19.** CLEAR fuel adjustments as described in Section S3.4.

## S7 Decomposition of overcrediting by parameter

As described in the main text, the decline from 9.24× (M1) to 1.60× (M17) decomposes on a log scale into approximately two-thirds science and rulemaking (principally fNRB) and one-third implementation (behavioural parameters and fuel measurement). Table S10 summarizes the approximate compound effect.

**Table S10:** Approximate compound effect of parameter corrections on sector-wide overcrediting. M1 uses GKH's original assumptions; M17 applies all implementation corrections with max(Bailis, 30%) fNRB.

| Factor | GKH (M1) | This study (M17) |
|---|---:|---:|
| Behavioural ($a \times u \times (1 - s)$) | ∼0.094 | ∼0.40 |
| Rebound | 0.78 | 0.78 |
| Fuel savings compression | ∼0.50 | ∼1.0 |
| fNRB asymmetry | ∼2.9 | ∼1.2 |
| Approximate compound | ∼9× | ∼1.6× |

# S8 Sensitivity and robustness

## S8.1 Project-level heterogeneity

Table S12 reports overcrediting ratios for all 51 projects under four key model specifications. Credits are highly concentrated: the five largest projects by VERs account for more than half of total issuance. No single project drives the sector-wide result; the largest projects (GS1094, VCS1216, GS2439) show dramatic reductions from M1 to M17, while metered projects (GS11509, GS11352, GS11507) start near parity and remain there across all specifications.

## S9 Supplemental figures

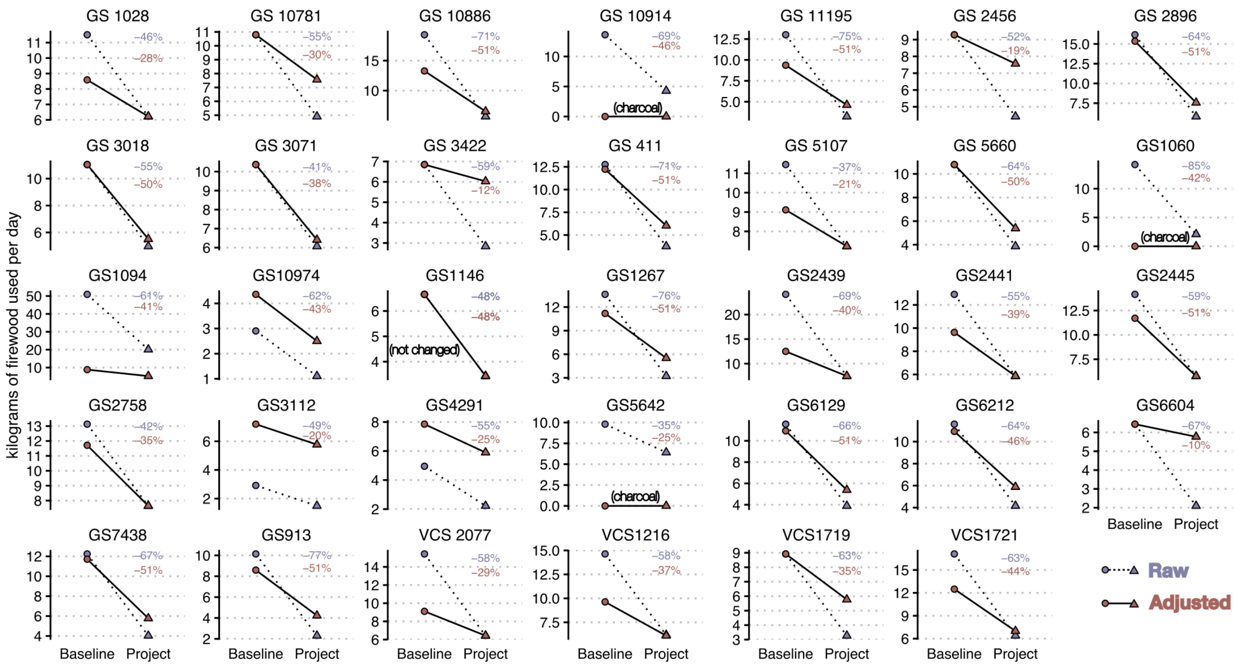


**Figure S1:** Placing bounds on 'reasonable' energy use systematically reduced apparent fuel savings in cookstove projects. Baseline and project fuel consumption estimates in kilograms of firewood used per day are shown from improved firewood cookstove projects. Adjustments were made by GKH so that both baseline and project fuel consumption estimates fit within a 'reasonable' range of energy consumption of 2–4 MJ/capita/day. In large part, baseline fuel consumption was lowered and project fuel consumption, when changed, was increased. Consequently, implied fuel consumption reductions were reduced. Purple annotations are raw (unadjusted) estimates of declines in fuel consumption due to project stoves and red are estimated fuel consumption declines following GKH's adjustments.

**Table S11:** Sensitivity of overcrediting estimates to fNRB data source. "Bailis 2015" uses regional defaults from Bailis et al. (2015), as in all main-text analyses. "Ghilardi 2024" replaces Bailis with country-level MoFuSS-modeled fNRB from Ghilardi & Bailis (2024). Δ is the absolute change; % is the percent change. All values are VER-weighted sector-wide overcrediting ratios.

| Scenario | Description | Bailis 2015 | Ghilardi 2024 | Δ | % change |
|---|---|---|---|---|---|
| S1 (cf. M1) | GKH replication | 9.24 | 9.25 | +0.01 | +0.1 |
| S2 (cf. M14) | fNRB = 30% both sides | 3.59 | 3.59 | 0.00 | 0.0 |
| S3 (cf. M15) | max(fNRB, 30%) practice gap | 8.04 | 8.06 | +0.02 | +0.2 |
| S4 (cf. M17) | Joint + max(fNRB, 30%) | 1.60 | 1.60 | +0.01 | +0.6 |

**Table S12:** Project-level overcrediting ratios across three key model specifications. Projects are ranked by total VERs issued (thousands). M1 = GKH replication; M11 = joint implementation corrections; M17 = all corrections with max(Bailis, 30%) fNRB. Values below 1.0 indicate undercrediting under that specification.

| Project | Per. | VERs (k) | M1 | M11 | M17 |
|---|---|---|---|---|---|
| GS1094 | 6 | 202 | 291.3 | 89.6 | 11.5 |
| VCS1216 | 24 | 142 | 56.2 | 17.2 | 3.17 |
| GS2439 | 6 | 111 | 9.99 | 7.50 | 1.59 |
| GS10974 | 4 | 92 | 52.7 | 1.31 | 1.03 |
| GS2441 | 8 | 92 | 131.3 | 98.5 | 2.05 |
| GS1267 | 6 | 90 | 6.51 | 4.88 | 1.03 |
| GS1060 | 6 | 75 | 30.7 | 9.43 | 7.14 |
| GS2094 | 12 | 56 | 31.3 | 9.62 | 4.44 |
| GS2758 | 6 | 46 | 73.5 | 3.49 | 2.33 |
| GS 2456 | 5 | 43 | 132.3 | 40.6 | 4.49 |
| GS5003 | 3 | 39 | 22.3 | 18.7 | 2.46 |
| GS6129 | 3 | 37 | 108.2 | 33.2 | 9.97 |
| GS2564 | 1 | 33 | 12.0 | 7.30 | 6.37 |
| GS 1028 | 5 | 32 | 107.5 | 33.0 | 10.8 |
| GS1146 | 4 | 29 | 9.66 | 7.62 | 4.92 |
| GS10884 | 2 | 28 | 1.86 | 1.73 | 1.25 |
| GS407 | 4 | 27 | 3.06 | 2.46 | 0.28 |
| GS7312 | 2 | 26 | 8.43 | 6.32 | 0.91 |
| GS 10886 | 1 | 26 | 12.5 | 9.41 | 2.38 |
| GS7438 | 2 | 23 | 32.8 | 24.6 | 21.3 |
| GS2513 | 1 | 18 | 9.94 | 9.60 | 3.16 |
| GS11509 | 1 | 13 | 1.38 | 1.08 | 0.41 |
| GS 10777 | 1 | 13 | 12.7 | 7.42 | 2.39 |
| GS 2896 | 1 | 13 | 47.3 | 14.6 | 6.77 |
| GS6212 | 2 | 12 | 19.4 | 5.97 | 1.81 |
| GS 5660 | 1 | 12 | 104.3 | 32.0 | 9.84 |
| GS 10781 | 1 | 12 | 80.5 | 24.8 | 5.21 |
| GS4677 | 1 | 12 | 3.94 | 3.79 | 3.13 |

**Table S12:** Project-level overcrediting ratios. *(continued)*

| Project | Per. | VERs (k) | M1 | M11 | M17 |
|---|---|---|---|---|---|
| GS11507 | 1 | 11 | 1.46 | 1.14 | 0.04 |
| GS500 | 1 | 11 | 39.7 | 43.6 | 30.3 |
| GS3112 | 4 | 11 | 27.7 | 8.51 | 1.70 |
| GS5642 | 2 | 10 | 14.6 | 7.03 | 8.85 |
| GS 11195 | 1 | 10 | 28.7 | 8.81 | 2.27 |
| GS7578 | 1 | 10 | 8.55 | 8.27 | 2.88 |
| GS 3018 | 3 | 9 | 9.33 | 2.87 | 5.73 |
| GS11352 | 1 | 9 | 2.00 | 1.57 | 0.47 |
| VCS1721 | 1 | 9 | 33.5 | 10.3 | 2.43 |
| GS 2077 | 1 | 9 | 73.4 | 22.5 | 2.15 |
| GS447 | 2 | 8 | 8.74 | 5.90 | 6.32 |
| GS2445 | 1 | 8 | 7.09 | 3.37 | 2.43 |
| GS913 | 1 | 8 | 29.8 | 9.14 | 1.65 |
| GS 411 | 1 | 7 | 24.6 | 7.57 | 1.45 |
| GS 3071 | 1 | 7 | 3.42 | 2.57 | 1.59 |
| GS 10914 | 1 | 6 | 13.1 | 4.03 | 4.44 |
| VCS1719 | 1 | 6 | 35.5 | 10.9 | 1.62 |
| GS 5107 | 1 | 5 | 20.1 | 15.1 | 3.45 |
| GS 11330 | 1 | 5 | 2.94 | 1.60 | 1.70 |
| GS4291 | 2 | 5 | 34.6 | 10.6 | 1.20 |
| GS 3422 | 1 | 4 | 81.6 | 25.1 | 3.17 |
| GS6604 | 1 | 3 | 81.8 | 25.1 | 0.91 |
| GS2744 | 2 | 3 | 152.9 | 46.7 | 2.41 |