

Aligning science, rulemaking, and practice to strengthen carbon crediting

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Abstract Results-based climate finance mobilizes private capital for climate mitigation by paying for verified outcomes¹. 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 gap⁹, 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 Correcting biased benchmarks and outdated science, we estimate credits exceeded actual reductions roughly fivefold.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 3.2 million people per year¹⁰, 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 CO₂e reduced^{1;11;12}. Recent evaluations suggest the accounting fails by large multiples—ninefold for cookstoves⁹, 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. More than two billion people burn polluting fuels for their daily energy needs¹⁶, and the resulting household air pollution kills roughly 3.2 million per year¹⁰. Carbon credits are one of the few mechanisms directing private capital toward cleaner alternatives where public finance does not reach^{17;18}. Gill-Wiehl, Kammen, and Haya (2024; hereafter GKH) found that credits from 51 such projects overstated actual reductions by $9.24 \times$ ⁹. Credit prices dropped, the Integrity Council for the Voluntary Carbon Market (ICVCM) flagged most cookstove methodologies¹⁹, 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 settings²⁰, making quantification accuracy the dominant integrity concern²¹.

Independent evaluations use outside data and explicit counterfactuals to test whether credited reductions actually occurred^{2;22}. Satellite imagery for forests^{4;13}, grid dispatch data for renewables³, and plant logs for industrial gases²³ 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 additionality¹⁴; and industrial-gas crediting created perverse incentives to overproduce waste gases^{23;24}. 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

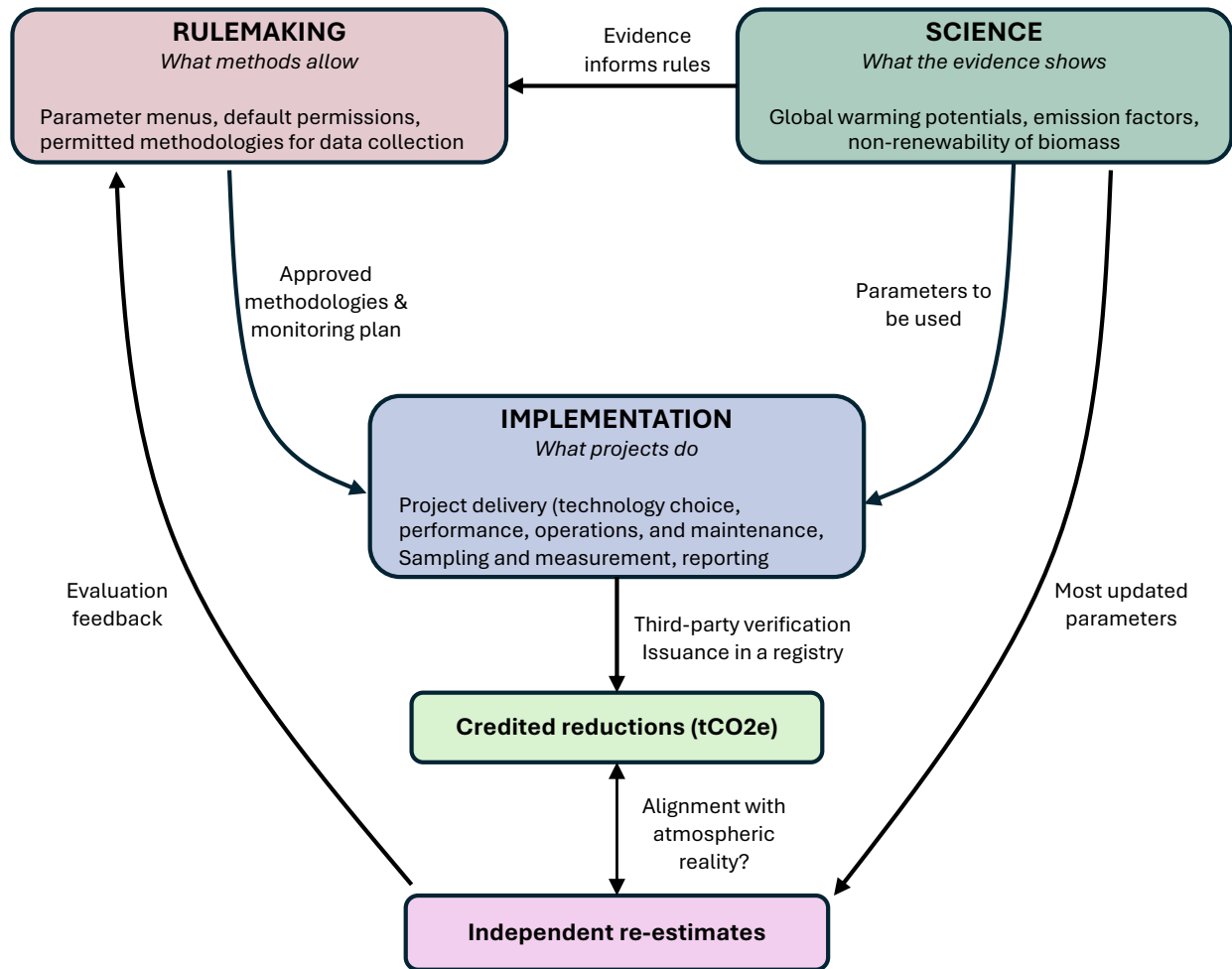


Figure 1: Carbon crediting as a sector-level system combining rulemaking, science, and implementation. An approved methodology and monitoring plan produces credited reductions (centre). Three upstream inputs shape credits: *Rulemaking* determines permissible parameters and whether measurement or defaults 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)^{25–27}. 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

Cookstove 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^{31–33}, and affordability, fuel access, device quality, and user preferences all shape whether use is sustained^{17;34;35}.

Crediting converts observed changes in cooking practices to avoided CO₂e 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 CO₂e 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.

Sector	Crediting basis	Threats to accurate crediting			Credit est. ^a	Share ^b
		Implementation	Rulemaking	Science		
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%

^aCredit est. = ratio of credited to independently estimated reductions (>1 = overcrediting). ^bCredit shares from the voluntary market, 2020–2024²⁸. ^cWest et al.⁴: 7% additional; Tang et al.¹³: 13%. ^dCames et al.¹⁴: 73% non-additional; Calel et al.³. ^eGKH⁹ → this paper; 9.24× → 5.05× after corrections. ^fOvercrediting ratio not applicable: credit value exceeded abatement cost, incentivizing waste-gas overproduction rather than reduction^{23,24}. EU banned HFC-23 credits in 2013. ^gFree-rider and rebound literature²⁹. ^hMethane model comparisons³⁰.

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)³⁶ are cited at 50% adoption though the study reports 90–95% active use; Burwen and Levine (2012)³⁷ 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^{35;38–42}, 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 CO₂e.

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^{43–45}. 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

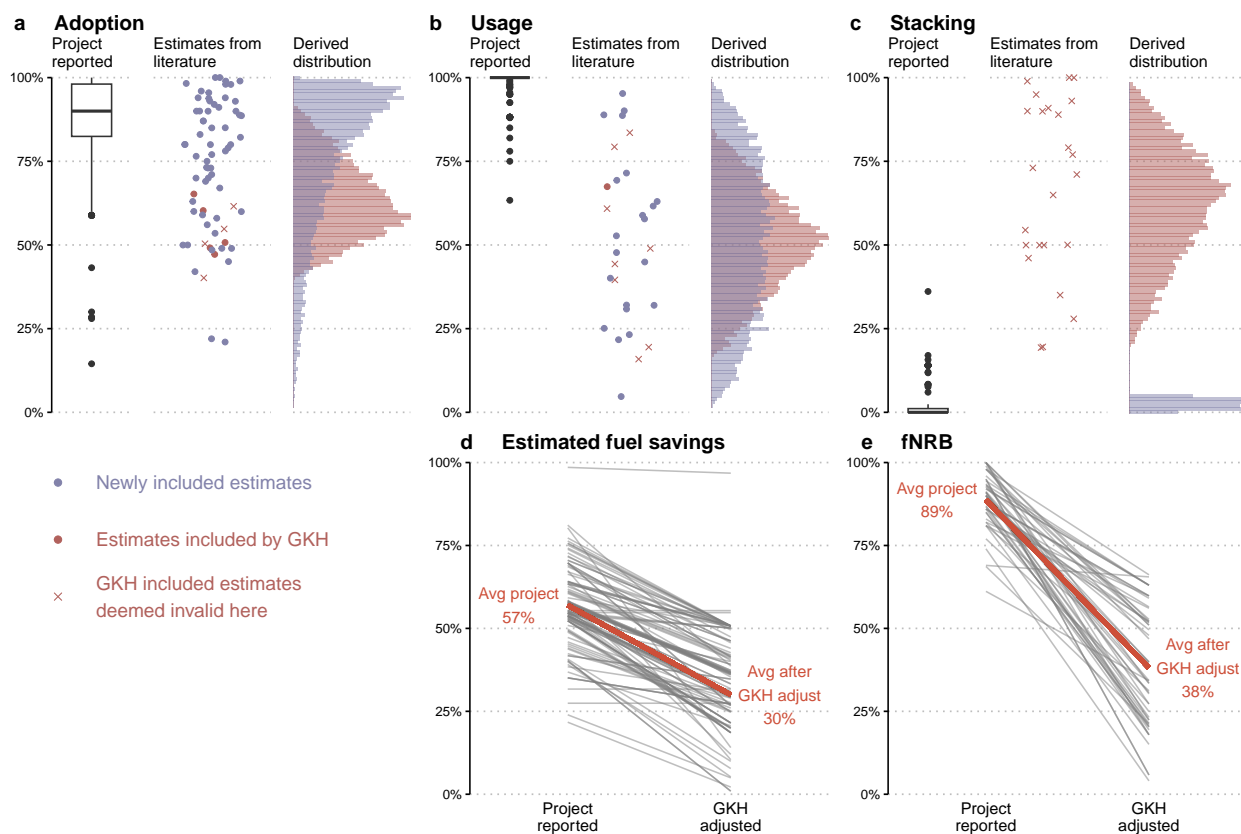


Figure 2: Widely used cookstove parameters in evaluations of the sector are biased low and poorly supported by evidence, and post hoc state-of-science references reduce credits. (a–c) Adoption, usage, and stacking estimates from GKH's literature review (red) compared to our expanded meta-analytic distributions (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 CO₂e, and has undergone substantial evolution over the past decade. Early practice often used national defaults of 80–90%⁴⁶. 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^{47;48}. 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 lacking¹⁹.

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^{49;50}. 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^{51–53}. 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 pro*

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 $\sim 87.5\%$ 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 $9.24\times$ to $8.04\times$ 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 $1.60\times$ (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 $9.24\times$ to $1.60\times$ 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 $5.05\times$, roughly 22 of the 27 Mt CO₂e these projects claimed to reduce did not actually occur.

Because most legacy cookstove credits were issued under the same default-based protocols

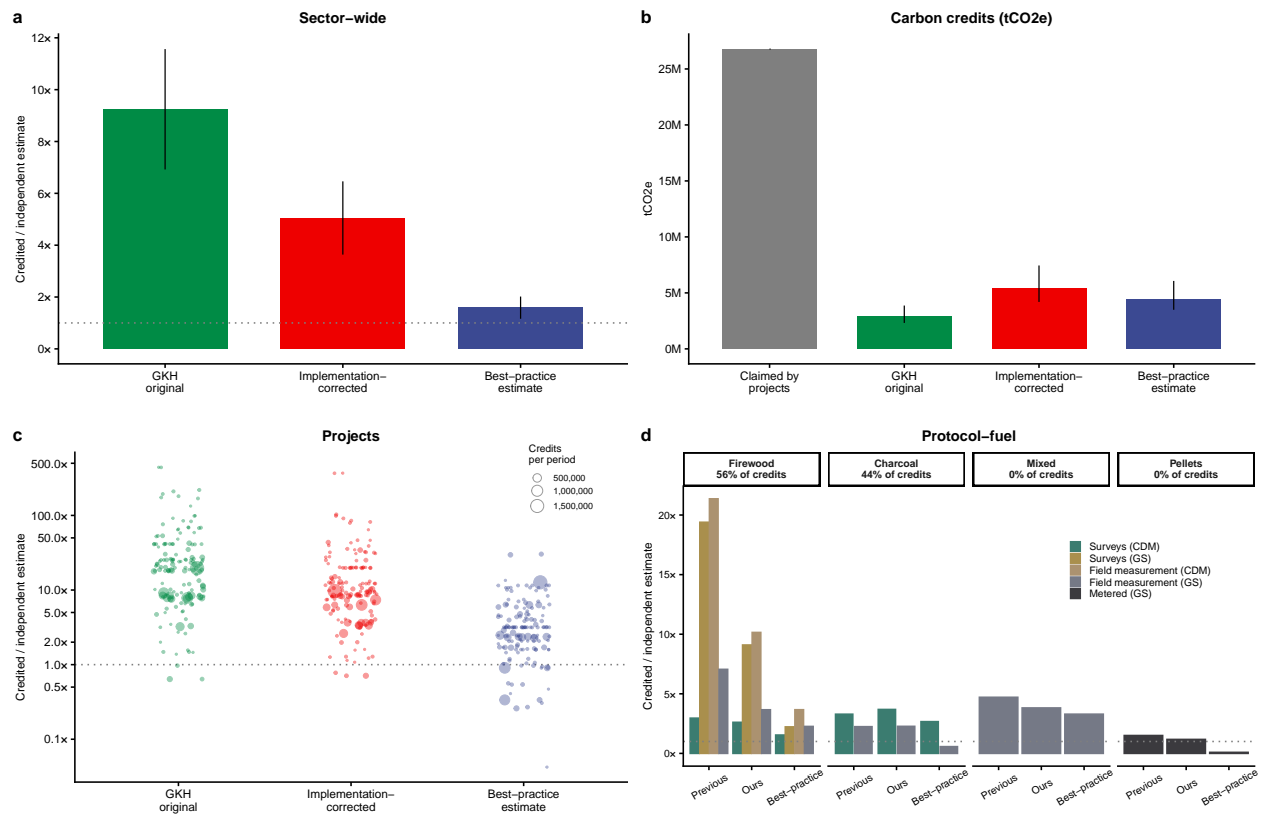


Figure 3: Alignment of cookstove project credited reductions with independent estimates: sector average, volumes, project dispersion, and protocol–fuel effects. (a) Sample-wide ratio of credited to independently estimated reductions: GKH’s original estimate (9.24×), our atmospheric estimate after implementation 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.

and CDM fNRB tool values, the patterns we identify likely extend beyond our 51-project sample (15% of the ~180 Mt issued to date²⁸). If they do, roughly 140 Mt of credited CO₂e reductions never actually occurred. At recent estimates of the social cost of carbon (\$185 per tCO₂⁵⁴ to above \$1,000 per tCO₂^{55;56}), 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, and 7.8 million across successive releases¹⁰. 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^{17;31}; 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 more than two 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^{49;50}; 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)⁴⁸, 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: $OC_{\text{sector}} = \sum_p \text{VER}_{s_p} / \sum_p (\text{VER}_{s_p} / \mathbb{E}[OC_p])$, where VER_{s_p} are verified credits and $\mathbb{E}[OC_p]$ 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.

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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

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Supplementary Information

Aligning science, rulemaking, and practice to strengthen carbon crediting

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Contents

S1 Review of GKH’s included studies and their appropriateness for providing estimates of adoption, usage, and stacking	S3
S1.1 Adoption	S3
S1.2 Usage	S8
S1.3 Stacking	S11
S2 Expanded literature review	S17
S3 Understanding fuel consumption adjustments	S24
S3.1 Assessment of GKH’s fuel adjustment approach	S28
S3.2 Ratio-preserving fuel consumption bounds (this study)	S30
S3.3 Projects excluded from ratio-preserving fuel adjustments	S31
S3.4 CLEAR fuel adjustments	S34
S4 Cookstove projects included in the study	S35
S5 Supplementary methods	S44
S5.1 Monte Carlo simulation design	S44
S5.2 Rebound correction	S44
S5.3 Sector-level aggregation	S45
S5.4 Confidence intervals	S45
S5.5 CLEAR energy consumption caps	S46
S6 Model specifications and results	S47
S6.1 Model descriptions	S50

S7 Decomposition of overcrediting by parameter	S51
S8 Sensitivity and robustness	S52
S8.1 Project-level heterogeneity	S52
S9 Supplemental figures	S53

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	<i>n</i>	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, $\text{Triangular}(0.193, 0.99, 0.673)$, 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
Pillariseti-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)
Jago-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
Pillariseti-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	<i>N</i>	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 $\text{kg} \times \text{NCV}$ (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 $W_{\text{baseline}}^{V1} = \min(W_{\text{baseline}}^{\text{adj}}, 4)$ and infer $W_{\text{project}}^{V1} = W_{\text{baseline}}^{V1} \times (1 - r)$. If project consumption falls below 2 MJ/capita/day, set $W_{\text{project}}^{V1} = \max(W_{\text{project}}^{\text{adj}}, 2)$ and infer baseline from r .
- **Model 9 (V2, cap project):** If project fuel consumption falls below 2 MJ/capita/day, set $W_{\text{project}}^{V2} = \max(W_{\text{project}}^{\text{adj}}, 2)$ and infer $W_{\text{baseline}}^{V2} = W_{\text{project}}^{V2}/(1 - r)$. 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 base-line	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 baseline (16.8 kg) is real FW	Reduced to 6.6 + added CH	GKH-adj	Raw PDD
GS4677	B	1	Ethanol; raw baseline (13.2 kg) is real FW	Reduced to 12.0	GKH-adj	Raw PDD
GS2094	C	12	“Charcoal as FW” in PDD treated as FW	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 base-line	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/charcoal
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/charcoal
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	Haggar Group / WDAN	GOLD	Standalone	GS Simplified	Sudan (North Darfur)	Community distribution	Firewood/charcoal
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/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 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	ECO 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 $j \in \{1, \dots, 10,000\}$ and each monitoring period $i \in \{1, \dots, 151\}$, 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 $\sim \text{Triangular}(0.40, 0.92, 0.58)$; Usage $\sim \text{Triangular}(0.16, 0.85, 0.52)$; Stacking $\sim \text{Triangular}(0.193, 0.99, 0.673)$.

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

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

where Δ_{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 ρ (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:

$$OC_{\text{sector}} = \frac{\sum_p VERs_p}{\sum_p (VERs_p / \bar{R}_p)} \quad (S2)$$

where $\bar{R}_p = E[VERs_p / VERs_p^{agw}]$ 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 :

$$R_j^{SDW} = \frac{\sum_p R_{pj} \times D_p}{\sum_p D_p} \quad (S3)$$

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

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

$$R_j^{ROS} = \frac{\sum_p VERs_p}{\sum_p VERs_{pj}^{agw}} \quad (S4)$$

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

S5.4 Confidence intervals

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

$$CI_{95} = [Q_{0.025}(R_1^{SDW}, \dots, R_{10000}^{SDW}), Q_{0.975}(R_1^{SDW}, \dots, R_{10000}^{SDW})] \quad (S5)$$

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
<i>Replication and Basic Corrections</i>							
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
<i>Behavioural Distribution Updates</i>							
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
<i>Fuel Consumption Adjustments</i>							
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
<i>Joint Implementation Corrections</i>							
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
<i>fNRB Sensitivity</i>							
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
<i>Combined Best Estimates</i>							
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
<i>CLEAR Methodology</i>							
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 $9.24\times$ (M1) to $1.60\times$ (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.

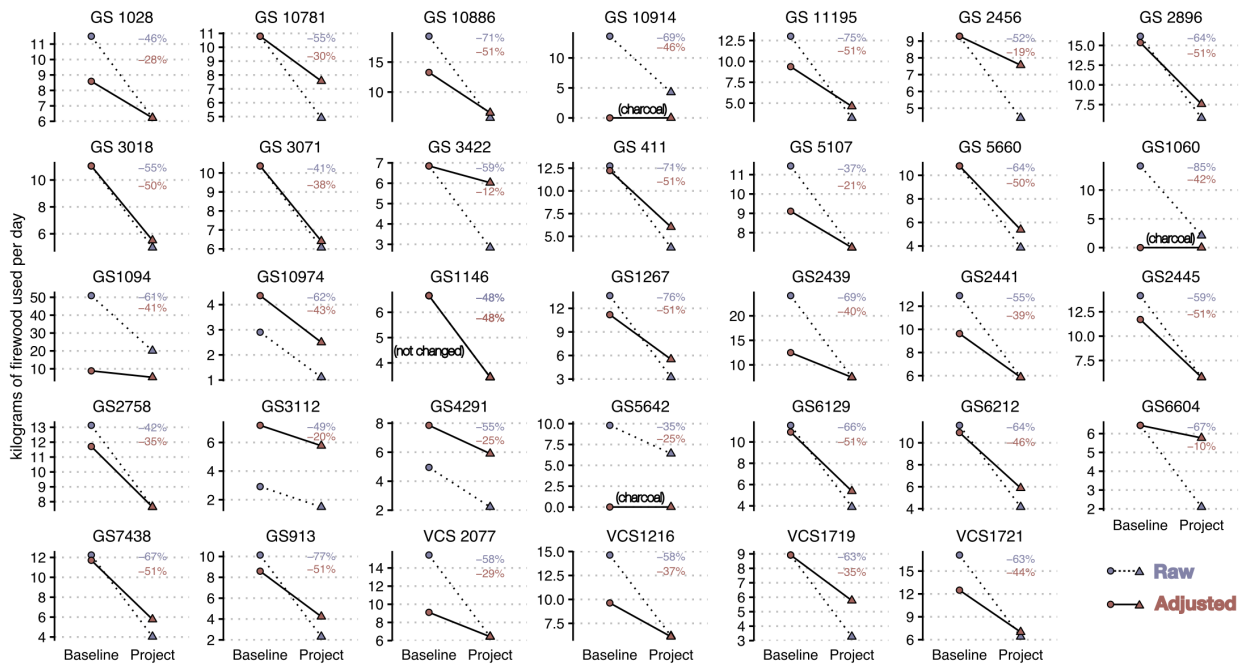
Factor	GKH (M1)	This study (M17)
Behavioural ($a \times u \times (1 - s)$)	~ 0.094	~ 0.40
Rebound	0.78	0.78
Fuel savings compression	~ 0.50	~ 1.0
fNRB asymmetry	~ 2.9	~ 1.2
Approximate compound	$\sim 9\times$	$\sim 1.6\times$

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: Fuel consumption scatter plot — to be generated.]

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