Methane leaks from natural gas systems follow extreme distributions

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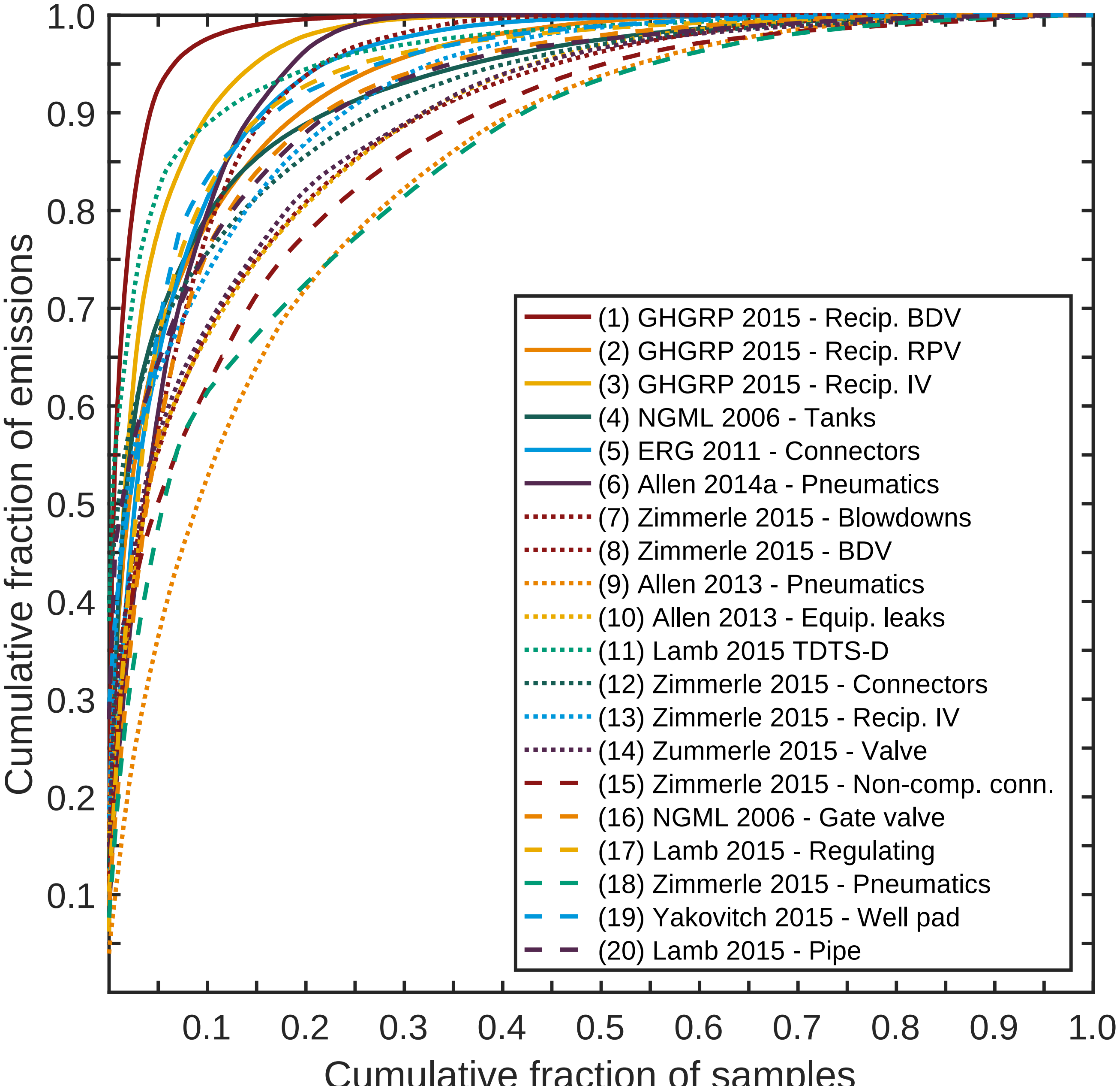
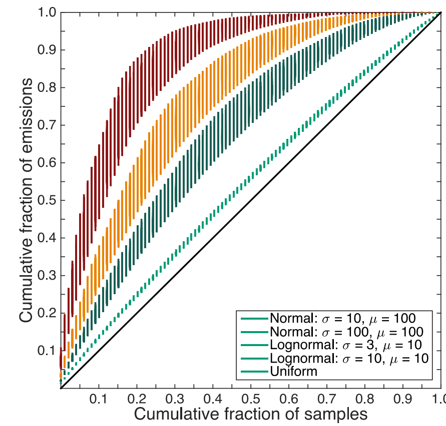
Background

Brandt, Heath, Cooley (2016). Methane leaks from natural gas systems follow extreme distributions. *Environmental Science & Technology.*

- Approached by Garvin and Adam, interested in heavy tails.
- Aim of Study: Identify, screen, re-classify and analyze existing datasets, investigate statistical approaches
  - 18 studies or datasets over 15 years
  - ~15,000 individual measurements
  - Device and facility level
  - Varied quantification methods: direct measurement, plume estimates and reported emissions

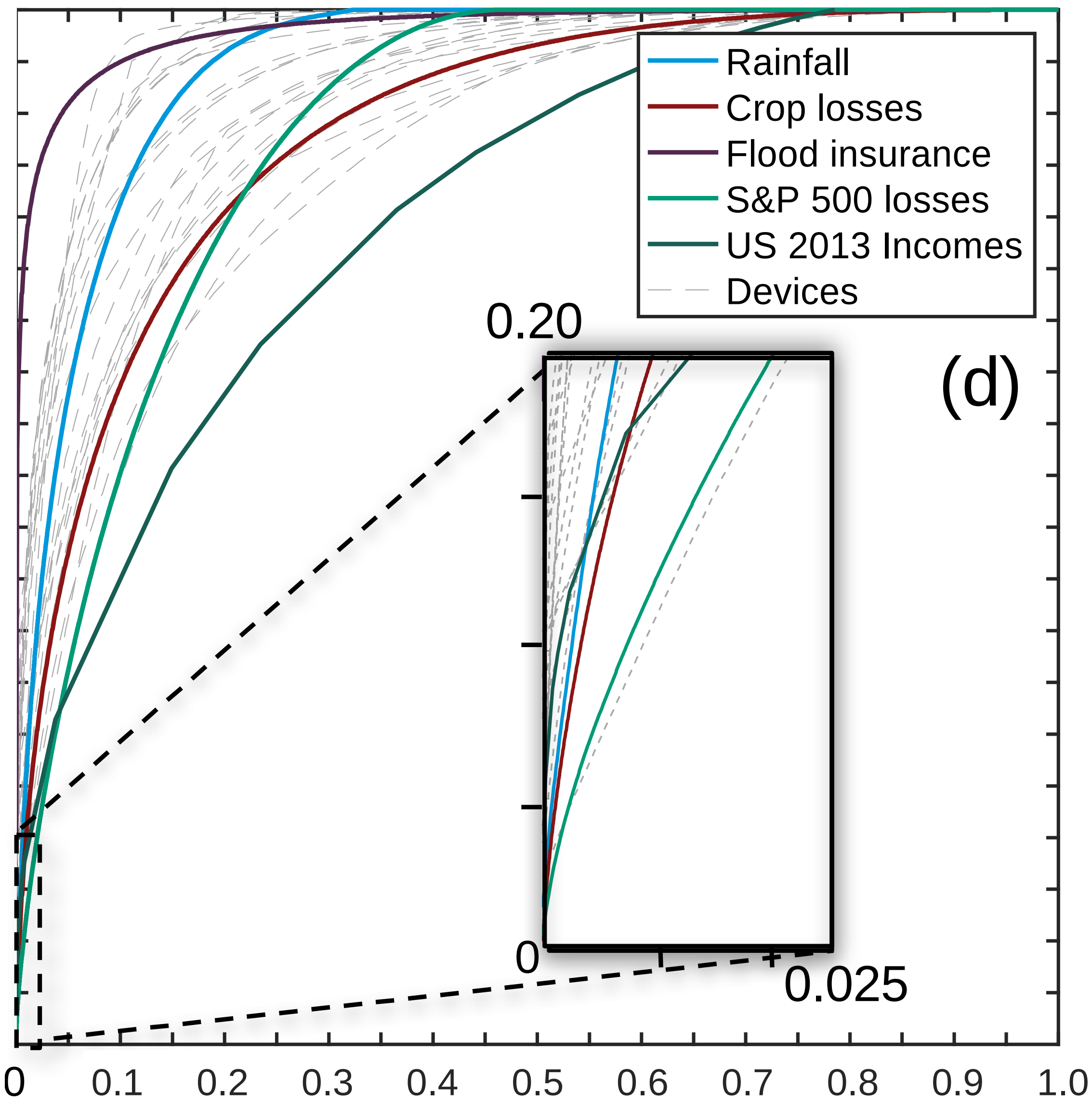
Grouping results by components (single-study)





Sample guide

Compared to other natural and social phenomena



More extremely distributed than things commonly known to be “heavy tailed”

Only observed dataset more extremely distributed is flood insurance claims.

Quantifying the tail: ξ

- A parameter which describes a distribution's tail.
- $\xi < 0$: distribution has an upper bound
- $\xi = 0$: unbounded decreasing exponentially
  - normal, gamma, *lognormal*
- $\xi > 0$: heavy-tailed, decays like a power function
  - $\xi > .5$ implies infinite variance, *usual stat methods don't work*

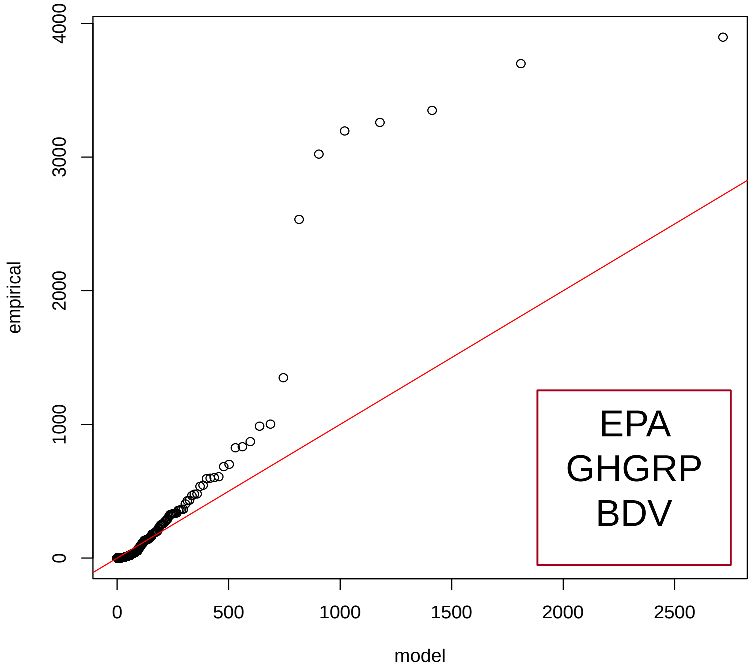
Data Source	ξ	*n*	95% CI
GHGRP BDV	0.77	2100	(0.46, 1.20)
GHGRP IV	0.25	1416	(-0.01,0.68)
GHGRP RPV	0.49	1532	(0.23, 0.88)

- point estimates for ξ are really large.
- ξ is hard to estimate, large uncertainty, small *n*
- Take away message 1: tails are *really* heavy

Uncertainty Quantification

Methods for confidence intervals:

1. T-based confidence intervals (assumes normal or CLT).
2. parametric bootstrap (requires distributional assumption).
3. nonparametric bootstrap (done by resampling).



Pitfalls of Parametric Bootstrap

1. Any distributional assumption is wrong.
2. Data in tail has limited “voice”.

Findings:

Fitted lognormal distributions underestimated the tail.

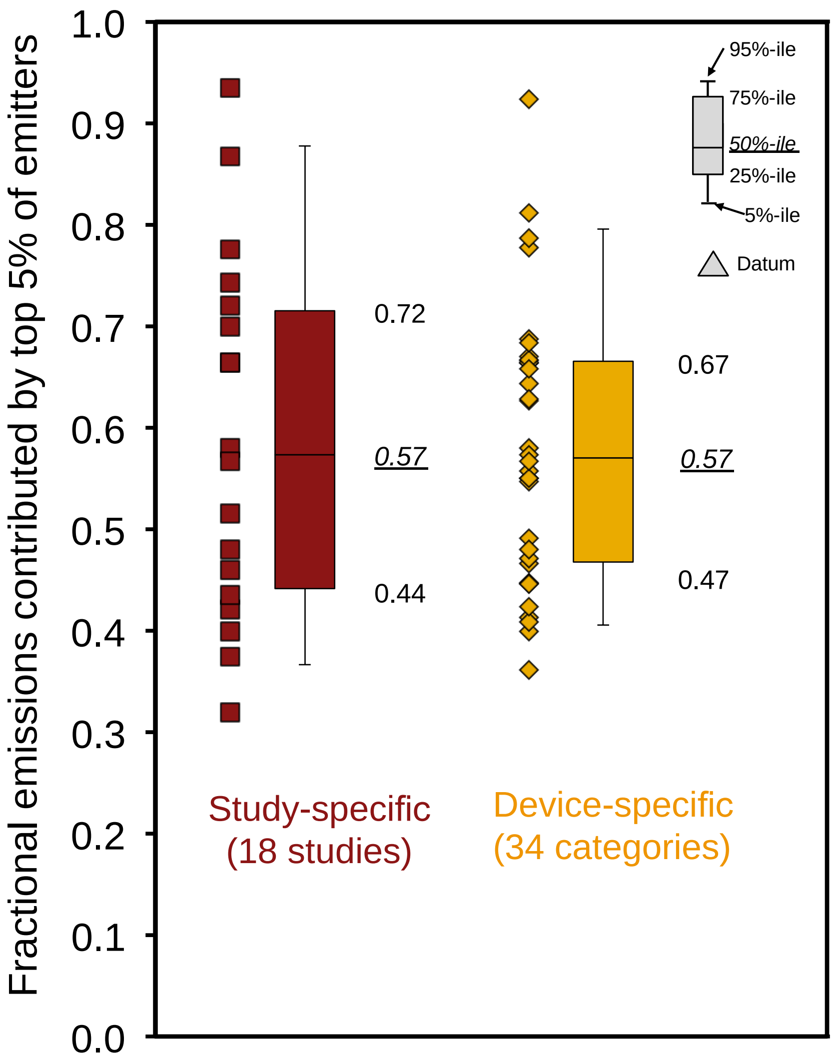
Bootstrap methods

- Nonparametric bootstrap
  - No distributional assumption
  - Performed by resampling (very simple)
  - However if $\xi > 0.5$, usual convergence doesn't hold

- GHGRP Blow-down-valve (BDV) data:
  - Mean estimate: 25.9 kg/day
  - Lognormal parametric bootstrap 95% CI:
    (20.3, 35.2) or (-22%, +36%)
  - Nonparametric bootstrap 95% CI:
    (18.89, 43.55) or (-27%, +68%)

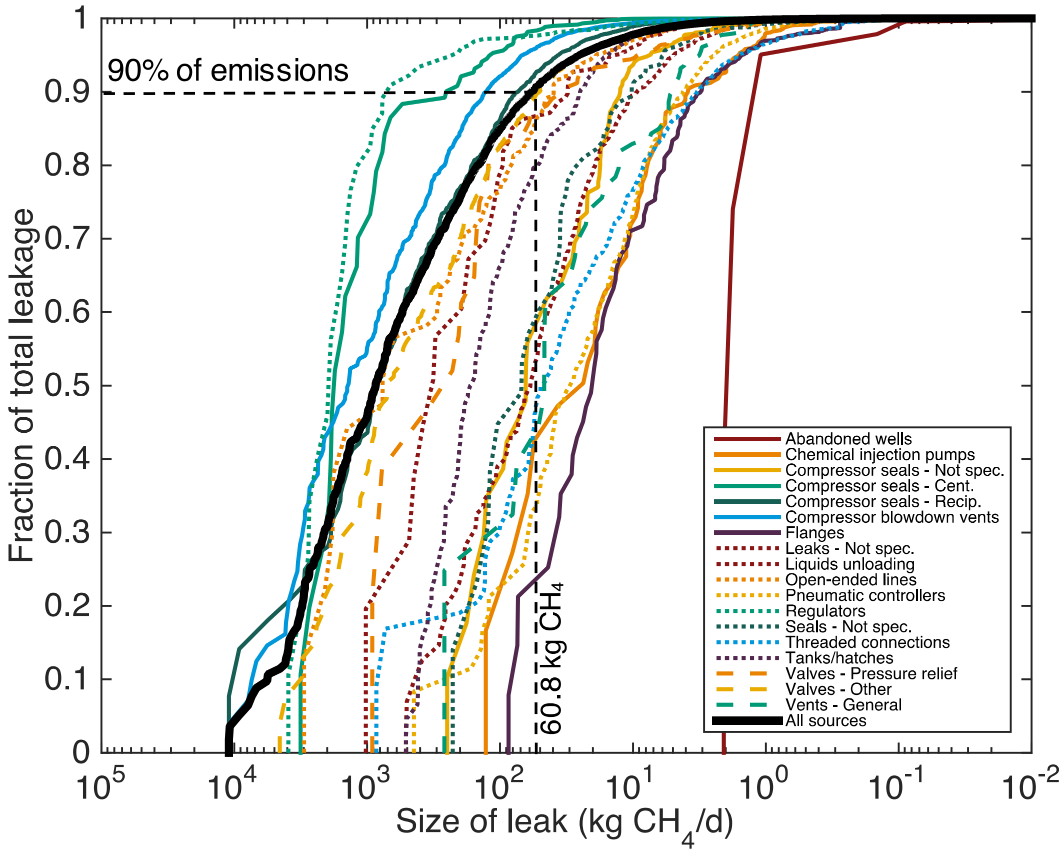
- Take Away Message 2: Heavy tails lead to greater uncertainty in mean estimates and have implications about how UQ should be performed.

Super-emitters



- Term “super-emitter” is becoming widely used, but its definition is not universal.
- Our paper’s definition: top 5% of emitters (also: Mitchell et al 2015).
- Key finding: Top 5% of sources with highest emissions contribute roughly 50% of emissions.
- Behavior seen universally across studies we analyzed.

Results: Super-emitters are not always large emitters



- 4+ orders of magnitude in range
- Median source in one category larger than super-emitter in others
- Take away message 3: Two-pronged strategy for mitigation
  - Focus on sources which are large emitters
  - Identify super-emitters

Sampling to estimate emissions factors

- Inventory approach:

  Emissions estimate = AF x EF
- EF should be obtained by taking sample mean of devices from a *representative sample.*
- Consider *sampling frame* for national emissions estimate: a (hypothetical) list of all the devices.
- Simple random sample would be obtained by random selection. Obviously this is impossible.
  – Expensive
  – Not all producers would allow measurements.
- Two further challenges:
  1. Combining data from different studies.
  2. Temporal behavior.

Can you combine different studies' data?

A: No. Or at least not easily.

KS tests of seven studies' "threaded connections" show all come from significantly different distributions. P-values all < 0.01.

	Kuo`12	NGML`06	Allen`13	Sub.`15	Zim.`15	Lamb`15
ERG 2011	0.000	0.000	0.005	0.000	0.000	0.000
Kuo 2012	--	0.000	0.000	0.000	0.000	0.000
NGML 2006	--	--	0.010	0.000	0.000	0.000
Allen 2013	--	--	--	0.000	0.001	0.002
Subram. 2015	--	--	--	--	0.000	0.000
Zimmerle 2015	--	--	--	--	--	0.000
Lamb 2015	--	--	--	--	--	--

Similar results across 5 device categories: only 3 of 28 pairwise comparisons failed to reject at p = 0.05 level.

Temporal aspects and sampling

- There is a mismatch between what is sampled and desired quantity to estimate.
- Sample: Instantaneous methane leakage *rates.*
- Estimate: Methane leakage amount (annual).
- What if rate isn't constant?
- Hypothesized some "superemitters" may be to planned maintainance.
- Contributing factor to top-down vs bottom up mismatch? (Emissions during work day.)
- How do you conduct sampling to account for temporal aspects? Think of sampling frame.

Take away message 4: Obtaining a representative sample for the purpose of estimating EFs is *really* hard.