Methane for Nothing: A Bayesian Meta-Analysis of Upstream Methane Emissions in U.S. Oil and Gas Production

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Abstract

The U.S. is the world's largest producer and exporter of liquefied natural gas (LNG). Exported LNG may displace coal in other countries, which may in turn lead to a net reduction in greenhouse gas (GHG) emissions. Methane emissions in the LNG supply chain are a key determinant of the net GHG impact of exported LNG over its lifecycle. I analyse 28 studies spanning more than a decade of data collection and 7 estimating methods, and perform a multi-level Bayesian meta-analysis to estimate methane emissions rates in 11 oil and gas producing basins, accounting for nearly 90% of U.S. gas production. I apply the meta-analysis results to compare the GHG emissions of exported LNG sourced from each basin, to coal in Asia assuming perfect substitution. I find that LNG sourced from at least 3 of the 11 basins studied has lifecycle GHG emissions exceeding that of Asian coal under some modeling scenarios, although the credible intervals around estimates are wide and there is variation under different scenarios.

Keywords: natural gas, lifecycle analysis, methane leakage, LNG, climate change, Bayesian meta-analysis

JEL: Q41, Q53, Q54, C11

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1 Introduction

Coal is the largest anthropogenic source of greenhouse gas (GHG) emissions, and a global energy transition from high GHG emission sources like coal to low- or zero-GHG sources will be a critical component of any plan to mitigate climate change. Most of today's coal demand, as well as projected future demand, comes from China, India, and, to a lesser extent, developing East Asian economies such as Vietnam and Indonesia (International Energy Agency 2024). An appealing strategy that allows for the abatement of coal alongside continued energy demand growth in these developing economies is the substitution of coal with alternate energy sources. Liquefied natural gas (LNG)[1] exported from the United States may be one such possible substitute, and a number of policy advocates, political leaders, and industry interests have advanced the case that increasing exports of U.S. LNG would lead to lower net GHG emissions (Bledsoe 2023; PAGE Coalition nd; American Petroleum Institute 2020; Vallas 2023). However, the marginal effect of increased U.S. LNG exports on global GHG emissions remains uncertain.

A supply shock of U.S. LNG may affect GHG emissions in an importing country[2] at the extensive margin through an increase in aggregate gas consumption, or at the intensive margin through displacement of other energy sources. One of the most important factors in comparing the net GHG effect of exported U.S. LNG to its possible substitutes, most importantly coal in China, India, and East Asia, is the rate of upstream methane emissions at the site of natural gas production, also known as fugitive methane. Methane is a highly potent GHG, 82 times more potent than carbon dioxide on a 20-year timeline[3] and 28.5 times more on a 100-year timeline

[1]LNG is natural gas that has been cooled to a liquid at special export terminals and loaded to ships and transported over long distances, where it is regasified and transported to end users through pipelines (U.S. Department of Energy nd).

[2]The same supply shock of U.S. LNG exports is likely to increase domestic natural gas prices, which also consequences for GHG emissions (Abuin 2025). I focus here on importing-country effects.

[3]Methane is a short-lived pollutant, with a half-life of approximately 10 years, so its climate

(U.S. Environmental Protection Agency 2025). Methane may be emitted during any stage of the LNG supply chain, including gas production ("upstream"), transmission, liquefaction, shipping, and local distribution after landing at its destination, with upstream leakage at the site of production generally being the largest source (Howarth 2024; Abrahams et al. 2015). Intuitively, because methane is such a potent pollutant, if methane emissions in the LNG supply chain are sufficiently high, GHG emissions from the lifecycle of LNG will be higher than those from coal. In this study, I discuss LNG-coal "breakeven" rates, which are rates of upstream methane emissions for natural gas production, at which exported LNG made from that natural gas would have the same GHG emissions as coal.

In this study, I characterize upstream methane emissions as a key determinant of the net impact of U.S. LNG exports on global GHG emissions. I specifically tackle the question of LNG-coal substitution, comparing upstream methane emissions rates to breakeven rates under a range of scenarios.

Methodologically, this study is a meta-analysis of empirical estimates of upstream methane emissions in the United States. Historically, U.S. Environmental Protection Agency (EPA) estimated this parameter through a "bottom-up" emissions inventory method, accounting for emissions from components of the natural gas production process with engineering models and self-reported data from firms. In recent years, there has been a profusion of research using remote sensing techniques, using satellites and aerial overflight, to measure methane emissions "top-down", finding much larger results than the EPA. However, these studies are not consistent in geographic coverage, scale, or method, and offer a wide range of estimates. The only study, to my knowledge, to synthesize past literature is Omara et al. (2018), which predates the significant recent expansion of the empirical literature.[4] Furthermore, in the absence

effects decay over time.

[4]While Yang et al. (2023); Vollrath et al. (2024) conduct broad reviews of trends in the literature, this is the first meta-analysis to quantitatively synthesize empirical results.

of a meta-analysis in the literature, models that require upstream methane emissions rate as an input tend to rely on individual studies (for example, Howarth 2024; Abuin 2025; Prest 2025), leading to the possibility of bias and arbitrariness in selection, to the exclusion of the rich scientific literature with varying methods.

Therefore, in this study, I explore the heterogeneity in upstream methane emissions rates in US oil and gas producing fields. I find that LNG sourced from at least 3 of the 11 basins studied has lifecycle GHG emissions exceeding that of Asian coal under some modeling scenarios, although the credible intervals around estimates are wide and there is variation under different scenarios.

The first major contribution of this study is to compile the largest (to my knowledge) dataset of upstream emissions rates in the U.S., and perform a multi-level Bayesian meta-analysis synthesizing them. The second major contribution of this study is to perform the first extraction and synthesis of LNG-coal breakeven rates, and the first comparisons of breakeven rates to empirical upstream methane emission rates.

A number of recent studies have sought to model the net emissions of LNG as compared to substitutes like Asian coal (Abuin 2025; Roman-White et al. 2021; Smillie et al. 2022), but have relied on single estimates of upstream methane emissions rates as inputs. The upstream methane emissions rate is also an important parameter in energy economics research beyond the LNG use-case, for example in modeling the response of U.S. hydrocarbon producers to changing oil prices (Prest 2025). Characterizing the upstream methane emissions rate in the United States is therefore the principal objective of this study.

This question is of significant policy relevance for decision-making, since there are several proposed LNG facilities awaiting permits from the U.S. government (U.S. Federal Energy Regulatory Commission 2025; Reuters 2025). It is also important in assessing the trajectory of aggregate global GHG emissions. First, U.S. natural gas prices are significantly and persistently lower than European and Asian benchmarks, (U.S. EIA 2020), motivating arbitrage through LNG export. Second, U.S. LNG exports have been growing rapidly, from zero exports before 2016 to becoming the world's largest exporter by 2024 (U.S. EIA 2025a), and are forecasted to continue to grow significantly over the next several years (U.S. EIA 2024). These facts suggest that U.S. LNG export volume is likely to be high and increasing, making it important to understand its net effect on GHG emissions.

Regional heterogeneity in upstream methane leakage is also of possible interest for differentiation of LNG by source, based on estimated emissions, for climate-conscious LNG consumers such as the Carbon-Neutral LNG Buyers Alliance (Yep and Kumagai 2021), or to comply with regulations in importing regions such as the European Union (International Energy Agency 2025).

I present an overview of the relevant scientific literature in Section 2 and of the data collection and analysis method in Section 3. I present results in Section 4, discuss implications in Section 5, and conclude in Section 6.

2 Literature Review

This study draws on two broad strands of literature. First, I refer to the scientific literature that estimates upstream methane emissions rates using direct measurement techniques. These studies rely on satellite data, aerial overflights, mobile laboratories, terrestrial towers, or past literature, to provide estimates of methane emissions from specific spatial regions. I refer to these studies and present summary statistics in Appendix A1.

Second, I refer to the literature of lifecycle analysis (LCA), which quantifies the GHG emissions attributable to various fuels. I focus on studies which compare the GHG emissions associated with U.S. LNG exports to Asia to those associated with coal produced and consumed in Asia, namely Abrahams et al. (2015); Roman-White et al. (2019); Feldman and McCabe (2024). These studies identify the upstream methane emissions rate has as a key parameter in determining net GHG impacts. Crucially, I focus on studies that conduct an "attributional" LCA, which assume perfect substitution between LNG and coal.[5] Using data from the scientific literature, they account for GHG emissions through the entire supply chain of LNG, from production to end-use, and compare those emissions with coal. These studies report "breakeven" rates, which are thresholds above which the net GHG emissions of U.S. LNG exceed those of Asian coal.

3 Methods

The parameter of interest in this analysis is the upstream methane emissions rate, defined as total methane emissions to the atmosphere from a particular basin, normalized by the methane content of the natural gsa produced in that basin.

$$\text{Upstream Methane Emissions Rate (\%)} = \frac{\text{Upstream Methane Emissions to Atmosphere}(kg\,CH_4)}{\text{Methane Content of Natural Gas Produced}(kg\,CH_4)}$$

I searched Google Scholar for empirical analyses of methane emissions from U.S. oil and natural gas production fields. I followed the references of relevant studies recursively to add to the dataset. While my dataset is not comprehensive, it is significant in size. An important limitation of my data processing method and model is that I calculate standard errors as the midpoint of asymmetric confidence intervals, thereby introducing some unavoidable model misspecification error. I provide further

[5] It is important to note that these are highly conservative estimates because they are predicated on a perfect-substitution assumption. More complex models which incorporate market dynamics such as imperfect substitution and extensive margin effects, namely Abuin (2025); Smillie et al. (2022), could also utilize the results of this study but do not report simple "breakeven" rates.

details on the selection and processing of this data in Appendix A2.

I estimate a three-level hierarchical Bayesian model of methane emissions rates at the basin level. I treat each basin as a fixed effect, and treat individual studies and data collection methods as random effects. I model each basin's prior upstream effect around a mean of a 2% upstream emissions rate. I provide further details on model setup and choice of priors in Appendix A5, and perform a sensitivity analysis to these choices in Appendix A8.

I directly extract "breakeven" rates from Abrahams et al. (2015); Roman-White et al. (2019) and select rates corresponding to roughly comparable scenarios. For Feldman and McCabe (2024), I impute a breakeven rate from their results by assuming a linear relationship between upstream emissions rate and corresponding GHG emissions. In all cases, I use breakeven rates that compare natural gas to coal on a 20-year timescale (U.S. Environmental Protection Agency 2025).[6] I provide further details of the process of selection of breakeven rates in Appendix A4. I compute the Bayesian posterior probability that the true emissions rate exceeds each breakeven threshold for each basin in my sample.

All analyses were performed using R Statistical Software version 4.4 (R Core Team 2024) using the *brms* package (Bürkner 2017).

4 Results

I locate a total of 28 unique studies in my initial survey. After applying exclusion criteria as discussed in Appendix A2, the final sample contains 58 unique estimates of basin-level methane emissions rates across 11 US oil and gas basins covering 6

[6] Methane emissions are the key variable under study, and methane has a higher global-warming impact than carbon dioxide, but is shorter-lived. Therefore, when comparing methane and other GHG emissions, the choice of the timescale matters. A 20-year timescale intensifies the apparent effects of methane relative to a 100-year timescale, but I have chosen to focus on the former because it corresponds to the timeline of policy-relevant commitments to GHG reduction such as the Paris Agreement (UNFCCC 2016).

methods. These 11 basins accounted for nearly 90% of U.S. natural gas production in 2023 (Raimi et al. 2025). I present a summary of basin-level Bayesian posteriors in Table 1. In Table 2 I report my final sample of breakeven rates for U.S. LNG exports

Basin	Estimate (%)	Est.Error
Anadarko	3.532	0.571
Appalachian	0.868	0.127
Arkoma	1.304	0.231
Denver	1.363	0.208
Fort Worth	3.022	0.451
Permian	4.088	0.627
San Juan	2.297	0.364
TX LA MS Salt	1.110	0.171
Uintah	2.423	0.387
Western Gulf	1.836	0.288
Williston	3.730	0.630
τ_{method} Between-Method SD	0.182	0.160
τ_{study} Between-Study SD	0.696	0.124
Residual SD	0.000	0.000

Table 1. Posterior Estimates of Basin-Level Methane Emissions Rates and Estimates of Standard Deviation Hyperparameters

Posterior estimates range from a 0.89% emissions rate in the Appalachian basin to a 4.09% emissions rate in the Permian basin. τ_{study}, the estimate of heterogeneity between studies, significantly exceeds τ_{method}, the estimate of heterogeneity between data collection methods in studies.

to have equivalent GHG emissions as Asian domestic coal. Table 2 details LNG-coal breakeven rates ranging from 0-6% across a variety of scenarios, most importantly whether the fuel is being used for industrial heating or power generation, and whether emissions from pipeline distribution of LNG after regasification in the destination country are included or not. In Figure 1, I plot the basin-level Bayesian posterior emission rates, and overlay vertical lines that depict the sample of breakeven rates. I report posterior probabilities of methane emissions exceeding breakeven thresholds in Appendix Table A3.

I find significant regional heterogeneity, with low methane emission rates in the

Source	LNG Destination	Comparison Fuel	End Use	Destination Pipeline Distribution	Breakeven Rate
Abrahams et al. (2015)	Europe/Asia	Domestic Coal	Industrial Heating	Yes	0.00%
Abrahams et al. (2015)	Europe/Asia	Domestic Coal	Industrial Heating	No	3.00%
Abrahams et al. (2015)	Europe/Asia	Domestic Coal	Power Generation	Yes	3.00%
Roman-White et al. (2019)	Shanghai	Domestic Coal	Power Generation	No	3.10%
Feldman and McCabe (2024)	Vietnam	Australian Coal	Power Generation	Yes	5.05%
Abrahams et al. (2015)	Europe/Asia	Domestic Coal	Power Generation	No	6.00%

Table 2. LNG-Coal Upstream Methane Emission Breakeven Rates

LNG sourced from natural gas with upstream methane emissions rates equal to the breakeven rates in the table, have equal lifecycle GHG emissions as Asian coal, under the scenarios corresponding to each breakeven rate. These rates range from 0% for industrial heating end-use, when accounting for emissions from importing country distribution pipelines, to 6% for power generation end-use, when not accounting for emissions from importing country distribution pipelines.

Denver, Arkoma, TX-MS-LA Salt, and Appalachian Basins, all below 1.5%, and high methane emission rates in the Permian, Williston, and Anadarko Basins, all exceeding 3.1%. These high-emission basins account for 28% of U.S. gas production (Raimi et al. 2025). According to Abrahams et al. (2015), LNG sourced from the Permian, Williston, and Anadarko Basins leads to higher GHG emissions than Asian coal when used for industrial heating, even when we do not account for emissions from distribution of LNG after regasification in importing-country pipelines, and leads to higher GHG emissions than Asian coal when used for power generation *only* when accounting for emissions from importing-country distribution pipelines, but lower GHG emissions than Asian coal when not accounting for importing-country distribution pipeline emissions. In contrast, Roman-White et al. (2019) suggest that

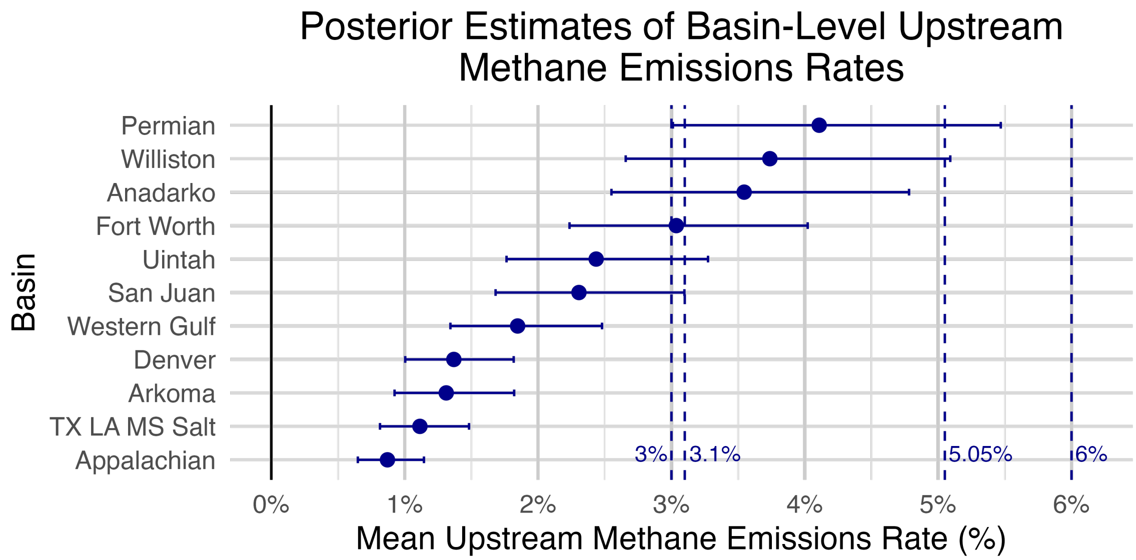

Figure 1. Posterior Estimates of Basin-Level Methane Emissions Rates with 95% CI and thresholds from Abrahams et al. (2015); Roman-White et al. (2019); Feldman and McCabe (2024)

in the latter scenario, LNG from these basins *would* have higher GHG emissions than Asian coal.

The Permian and Williston Basins have 95% credible intervals that overlap with the 5.05% threshold from Feldman and McCabe (2024), suggesting that LNG from these basins could potential lead to higher GHG emissions in Vietnam, when compared to Australian coal, when considering importing-country distribution emissions and power generation end-use.

5 Discussion

The presence of basin-level heterogeneity in upstream methane emissions rates suggests that the net GHG emissions impact of U.S. LNG exports will depend on elasticities of supply and the heterogeneous production response of producers in different basins. If high-methane-emission basins meet the increased natural gas demand for LNG exports, net GHG emissions are likely to be higher, and potentially higher than

Asian coal. Notably, the Permian and Williston basins, with high upstream methane emissions rates, are experiencing significant growth in natural gas production volume (U.S. EIA 2023b).

Further, basin-level upstream methane emissions rates may respond dynamically to changing prices and increased supply due to heterogeneity between producers within a basin (Lyon et al. 2021). Relatively new natural gas production facilities may have higher methane emissions than older ones (Schneising et al. 2020a; Irakulis-Loitxate et al. 2021; Zhang et al. 2020). Older, conventional gas production may have significantly higher methane emission rates than newer shale gas production (Omara et al. 2016). On the other hand, aggregate emission rates may decrease over time (Lu et al. 2023) due to regulations or the construction of infrastructure to allow for methane that would otherwise be emitted to be captured.

6 Conclusion

I conduct a three-level Bayesian meta-analysis of upstream methane emissions rates in U.S. oil and gas production basins, and compare Bayesian posterior estimates of basin-level rates to breakeven thresholds from the literature, corresponding to emissions rates where the net lifecycle GHG emissions of LNG are equivalent to those of coal. I treat LNG as perfect substitutes for Asian coal and find that even under this conservative assumption, with substantial regional heterogeneity, high-emission basins such as the Permian, Williston, and Anadarko exceed some breakeven thresholds, making them worse for the climate than coal under some scenarios. In contrast, low-emission basins such as the Appalachian and Arkoma are safely below all breakeven thresholds. Future research could use the Bayesian methods in this paper to incorporate the full range of methane emissions estimates in the literature in more sophisticated models which factor in extensive margin and imperfect substitution effects. Future research could also use this method to meta-analyse other key sources of methane emissions from the rest of the LNG and coal supply chains.

7 Supplementary Data

All data and code associated with this study are available in an online repository (Sud 2025).

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Appendix

A1 Scientific Literature Synthesized

Studies I have included in this meta-analysis, ordered alphabetically by author name, are Barkley et al. (2017, 2022); Chen et al. (2022); Hmiel et al. (2023); Karion et al. (2015, 2013); Lin et al. (2021); Lu et al. (2023); Lyon et al. (2021); Omara et al. (2016, 2018); Peischl et al. (2015, 2016, 2018); Pétron et al. (2014); Ren et al. (2019); Robertson et al. (2017); Roest and Schade (2017); Schneising et al. (2020b); Shen et al. (2022); Sherwin et al. (2023); Varon et al. (2022); Yacovitch et al. (2017); Zhang et al. (2020).

I present a summary of number of studies included along different categories in Table A1 and group-level means and confidence intervals in Table A2. I present a complete inventory of the studies included in the Supplementary Data.

Table A1. Summary counts of estimates, studies, methods, and basins.

Category	Count
Number of Estimates	58
Number of Studies	21
Number of Methods	6
Number of Basins	11

Table A2. Mean and confidence intervals of upstream methane emissions rates, grouped by basin and method

		Emission Rate (%)		
Type	Group	Mean	LCI	UCI
Basin	Anadarko	3.44	2.38	4.23
	Appalachian	0.75	0.46	1.18
	Arkoma	2.17	1.25	3.12
	Denver	2.67	1.78	3.49
	Fort Worth	2.35	1.78	2.89
	Permian	3.66	2.61	4.62
	San Juan	3.63	2.55	4.48
	TX LA MS Salt	1.29	0.86	1.71
	Uintah	5.20	3.96	6.39
	Western Gulf	1.87	1.27	2.56
	Williston	4.79	3.21	6.59
Method	Aerial	2.79	1.83	3.82
	Aerial+Tower	2.60	1.90	3.30
	Air quality monitor network	1.00	0.70	1.60
	Satellite	3.18	2.32	3.96
	Synthesis	1.90	1.17	2.60
	Tower	3.46	2.93	3.98

A2 Study Inclusion and Data Processing Method

During my recursive online search for empirical upstream methane emissions rate estimates, I include studies of all sizes that I find. The level of geographical aggregation varies – studies variously provide estimates at the national level, state level, basin level, at the sub-basin level, or at the level of a "shale play," which is a localized accumulation of hydrocarbon resources within an area of a basin. The initial sample of studies, with each individual estimate counted as an observation, includes 88 basin-level observations and 8 national-level observations.

I treat all levels at the basin and below to be representative of the basin. I choose this level aggregation for simplicity, while noting that this may introduce some error. Many studies report data for multiple basins, and I include all data points from each study I find. I manually classify the location of each study into a basin, based on reviews of the studies and comparisons with US EIA maps. (U.S. EIA 2023a)

I drop all national-level observations, since the objective of this study is to characterize basin-level heterogeneity in methane emissions rates.

I include studies with heterogeneous methodologies, including bottom-up emissions inventory approaches, satellite, aerial overflight, terrestrial tower measurements, and terrestrial mobile lab measurements. I manually classify each method into a method category. One study I include, Omara et al. (2018), is itself a literature synthesis study. To ensure that there is no duplication, I remove studies from my sample which were included in Omara et al. (2018).

To enable the primary Bayesian analysis, I exclude estimates without any confidence intervals published, which is relevant for all estimates from Shen et al. (2022) except their estimate of the Permian basin. I exclude any basins which have 2 or fewer studies providing estimates, leaving a final sample covering 11 basins.

The years of publication of studies included span a decade, from Karion et al. (2013) to Sherwin et al. (2023), while the years of data collection range from 2010-2023.

Where necessary, I converted the outcome variables in studies to a methane emissions rate with the consistent assumption of a 90% methane content of natural gas. In certain cases, the outcome variable was a raw quantity of methane in teragrams (Tg), which I divided by the average natural gas withdrawal in the relevant region and time period, drawing data from the U.S. Energy Information Administration (U.S. EIA 2025b). In the final sample, this recalculation was only relevant for Shen et al. (2022).

To allow for the logarithmic transformation of the lower confidence interval in Ren et al. (2019), I replace the zero value observed with a small positive number (10^{-6}).

Many data points have asymmetric confidence intervals. An important limitation of my current method is that I cannot incorporate this asymmetry. Instead, I estimate the standard errors using

$$SE = \frac{\text{Upper CI} - \text{Lower CI}}{2\,\Phi^{-1}(0.975)}$$

The different studies have different methods of arriving at these confidence intervals, and so the assumption of a normal distribution centered around the reported mean necessarily carries with it some model misspecification error.

A3 Basin-Level Analysis

In this study, I focus on characterizing upstream methane emissions at the level of geologic basins. This spatial heterogeneity provides one way of understanding the range of methane emissions rates associated with U.S. natural gas production. Ultimately, methane emissions rates and elasticities of supply are determined by individual firms and production sites. However, geologic basins are a useful (and conventional) unit of analysis, because producers within a basin face similar production decisions, physical hydrocarbon reserves, infrastructure availability, and state-level regulations. In the context of increased LNG exports as a demand shock to natural gas producers, basin-level characteristics will be an important determinant of the supply response of U.S. producers (Prest 2025), and consequently basin-level methane emissions rates are a useful intermediate parameter in assessing expected changes in GHG emissions.

A4 Breakeven Rates Drawn from Lifecycle Analysis Literature

In this section, I provide a detailed review of the lifecycle analysis literature as it pertains to the present meta-analysis. The three most relevant studies, which supply breakeven rates that are usable in this study, are Abrahams et al. (2015); Roman-White et al. (2019); Feldman and McCabe (2024).

Abrahams et al. (2015) conduct an attributional lifecycle analysis (LCA) of U.S. LNG exports, assessing the GHG emissions of each stage of the supply chain and comparing it to the lifecycle GHG emissions of coal in Europe or Asia. They conduct a sensitivity analysis that considers a range of upstream methane emissions rates, and find "breakeven" rates where the GHG emissions for U.S. LNG exports are comparable to their substitutes, under various assumptions. For example, a key assumption is whether or not the LCA factors in the GHG emissions associated with pipeline distribution of LNG in the importing country. Without accounting for these emissions, a 6% upstream methane emissions rate puts U.S. LNG on par with European or Asian domestic coal, when used for power generation. In contrast, when local distribution is considered, the corresponding breakeven rate for power generation is 3%.

Roman-White et al. (2019) similarly conduct an attributional LCA of U.S. LNG exports against their potential substitutes, and finds a lower range of breakeven rates than Abrahams et al. (2015). For example, they find a 3.1% breakeven rate for U.S. LNG exported to Shanghai as compared to domestic Chinese coal. They do not factor in emissions from importing country pipeline distribution of LNG.

Finally, Feldman and McCabe (2024) conduct a LCA of coal and LNG exports to Vietnam for power generation and consider three upstream emissions rates for natural gas, corresponding to the U.S. average, Permian, and Appalachian basins, drawn from Shen et al. (2022). They find that Permian gas, but not U.S. average or Appalachian-sourced gas, exported as LNG is worse than Australian coal. With a linear interpolating between the Appalachian and Permian upstream rates used, I impute the breakeven rate in Feldman and McCabe (2024) to be 5.05%.

In addition to the above studies, there are a number of other LCAs comparing U.S. LNG to Asian or European coal, although they do not yield usable breakeven rates for the present meta-analysis. I provide a brief survey of this literature below, in chronological order. Roman-White et al. (2021) conduct a supplier-specific attributional LCA, finding significant GHG reductions from coal-to-LNG switching for a particular supply chain from the U.S. to China, conditional on a low 0.65% total methane emissions rate (including upstream as well as other components of the chain). Rosselot et al. (2021) use a mix of satellite estimates in the Permian basin and inventory methods of East Texas to compare "high emission" and "low emissions" scenarios for both U.S. LNG and Chinese coal for electricity generation in China, finding that "high emission" U.S. LNG has higher GHG emissions than Chinese coal.Howarth (2024) conducts an attributional LCA using a 2.8% upstream methane emissions rate drawn from Sherwin et al. (2024)'s estimate for the Permian basin in the U.S., finding the potential for large increases in net GHG emissions from U.S. LNG exports to China. Zhu et al. (2024) compare net GHG emissions of LNG produced in the Appalachian (Marcellus shale) and Permian basins when modeling export to the UK and China. They rely on a limited set of relatively older studies for upstream methane emissions rates, namely Barkley et al. (2017) and Zhang et al. (2020), and find that the higher methane emissions of the Permian drive higher net GHG emissions.

Furthermore, there is a small number of studies which go beyond the conventional attributional LCA framework of all studies listed above. The key drawback of attributional LCA studies is that they assume perfect substitution of LNG for coal, neglecting all other effects. However, there are many channels through which exported U.S. LNG may affect GHG emissions. For example, substitution for renewable energy sources or nuclear power (Gilbert and Sovacool 2018) or even conventionally-produced Chinese natural gas (Gan et al. 2020) may lead to increased GHG emissions. A wide range of other issues that may affect the net GHG consequences of coal-to-gas switching, such as infrastructure lock-in (Abuin 2025; Leclair 2025). At the extensive margin, if the constraint on US LNG export capacity is lifted, with non-zero demand elasticity we can expect an expansion of total gas consumption, leading to potential increase in total GHG emissions (for example, U.S. Department of Energy 2023).

To my knowledge, the only studies that realistically model market effects of U.S. LNG exports are Smillie et al. (2022), which finds the marginal effect of new LNG export capacity to have highly uncertain effects depending on the various elasticities of fuel demand and supply, and Abuin (2025), which builds a dynamic global investment model and finds a net decrease in emissions through 2070 due to substitution towards renewables in the US, accompanied by substitution away from coal and delayed global renewables adoption.

A5 Detailed Bayesian Model Setup and Choice of Priors

This section contains the details of the setup of the Bayesian multi-level model used in the primary meta-analysis of this study, as well as specific choices of priors.

First, I motivate the decision to model basins as fixed effects, and studies and methods as random effects.

Each basin has unique characteristics that are likely to determine its true methane emissions rate, such as whether it is primarily an oil or gas producing region, the extent of available infrastructure for transport of natural gas, state-level regulations on methane emissions (for example, Reuters 2023), and the distribution of producers in a basin by age (Schneising et al. 2020a; Irakulis-Loitxate et al. 2021; Zhang et al. 2020), scale (Omara et al. 2022), and voluntary compliance. Therefore, I treat each basin as a fixed effect.

Studies in my final sample rely on different data collection methods, which may lead to heterogeneity in the true methane emissions rate, so I treat it as a random effect. Finally, even when accounting for variation in basins and methods, authors make analytical choices that lead to variation in the true estimate for each of them, such as the years in which they collected data, the resolution of their spatial grid, or the particular sites or sub-regions within a basin that they chose. Therefore, I model each study as a random effect.

Next, I present the mathematical formalism of the Bayesian model.

For each observation in each study, point estimates are represented y_{ijkm}, where the logarithm of each data point i from study j in basin k done with method m is modeled as drawn from a normal distribution. I apply a log transformation because the point estimates are rates, bounded below by zero. I convert the reported confidence intervals in each study to a study-level standard error σ^2_{ijkm}.

$$\ln y_{ijkm} \sim \mathcal{N}(\theta_{ijkm}, \sigma^2_{ijkm}) \tag{A-1}$$

The study level mean is in turn modeled as the sum of effects of the true basin-level emissions rate μ_k, method-specific random effects γ_m, study-specific random effects a_j, and an error term ϵ_{ijkm}.

$$\hat{\theta}_{ijkm} = \mu_k + \gamma_m + a_j + \epsilon_{ijkm} \tag{A-2}$$

Each of these effects (of basin, study, and method) is modeled as drawn from distributions with priors $\mu_k \sim \mathcal{N}(\ln(2\%), 0.7)$, $\gamma_m \sim \mathcal{N}(0, \tau^2_{\text{method}})$, $a_j \sim \mathcal{N}(0, \tau^2_{\text{study}})$. This prior on each basin-level emission rate approximates the U.S. EPA estimate of upstream methane emissions, and the 95% CI on the prior distribution ranges from 0.05% to 8%, reflecting my belief on a reasonable range of basin means. The random-effects hyperparameter priors are set to be weakly informative:

$$\tau_{\text{method}}, \tau_{\text{author}} \sim \text{Half-Cauchy}(0, 0.5)$$

Posterior estimates are exponentiated to transform them back to the original scale.

A6 Probabilistic Results

In Table A3, I evaluate the probability that the upstream methane rate of each basin exceeds a given coal breakeven threshold.

	Prob. Exceeding Threshold				
Basin	0%	3%	3.1%	5.05%	6%
Anadarko	*100*	*82.4*	*77.1*	1	0
Appalachian	*100*	0	0	0	0
Arkoma	*100*	0	0	0	0
Denver	*100*	0	0	0	0
Fort Worth	*100*	49.9	41.3	0.1	0
Permian	*100*	*97.3*	*95.9*	7.1	0.5
San Juan	*100*	3.7	2.2	0	0
TX LA MS Salt	*100*	0	0	0	0
Uintah	*100*	7.3	4.7	0	0
Western Gulf	*100*	0.1	0.1	0	0
Williston	*100*	*88.7*	*84.8*	2.8	0.2

Table A3. Posterior Probabilities that Basin Emission Rates Exceed Specified Thresholds. Italics where probabilities exceed 50%.

A7 Model Analysis

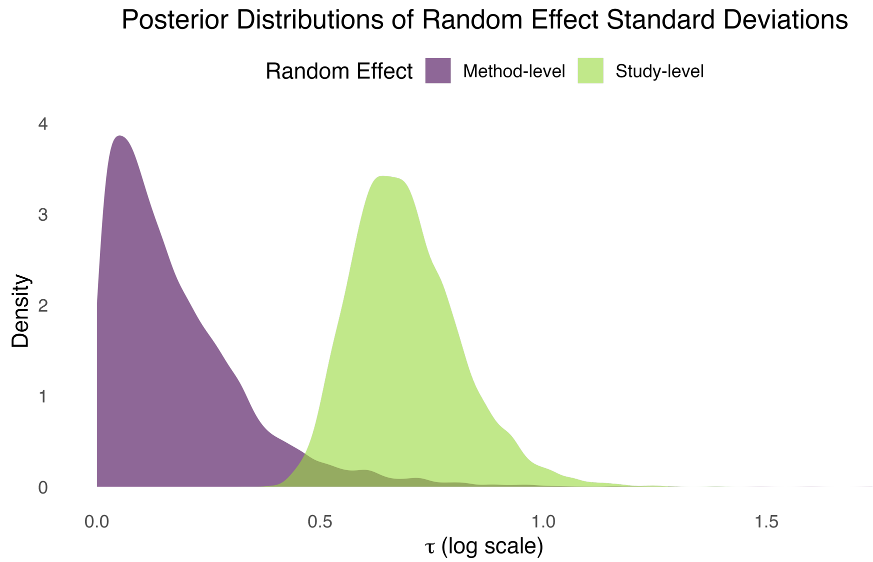

Figure A1. Posterior Standard Deviations of Random Effect Standard Deviations

This figure shows the posterior distributions of the τ hyperparameters, which correspond the standard deviations of the study and method random effects in the Bayesian model. These hyperparameters measure heterogeneity in methane emission rates between studies and between methods, respectively. The study-level standard deviation significantly exceeds the method-level standard deviation.

A8 Sensitivity Analysis

In the primary model specification, the basin is treated as a fixed effect while study and method are treated as random effects. In this section, I test alternative specifications to understand the robustness of the model.

In the first alternative specification, I consider study method as a fixed rather than random effect. There are some methods with a small number of associated studies, such as air quality monitoring networks ($n = 1$), tower measurements ($n = 3$), and aerial and tower combined ($n = 3$). I model method as a fixed effect to account for the possibility that I have too few studies to accurately estimate between-method variance, following guidance by Dettori et al. (2022). Under this model, I assume that there is no heterogeneity between methods, and all methods are estimating the same true upstream methane emissions rate.

Results from this specification are shown in A2. The effect of this change is to significantly widen all credible intervals, which is to be expected since we have added six new method parameters to the model. The point estimates for all basins increase relative to the primary model specification.

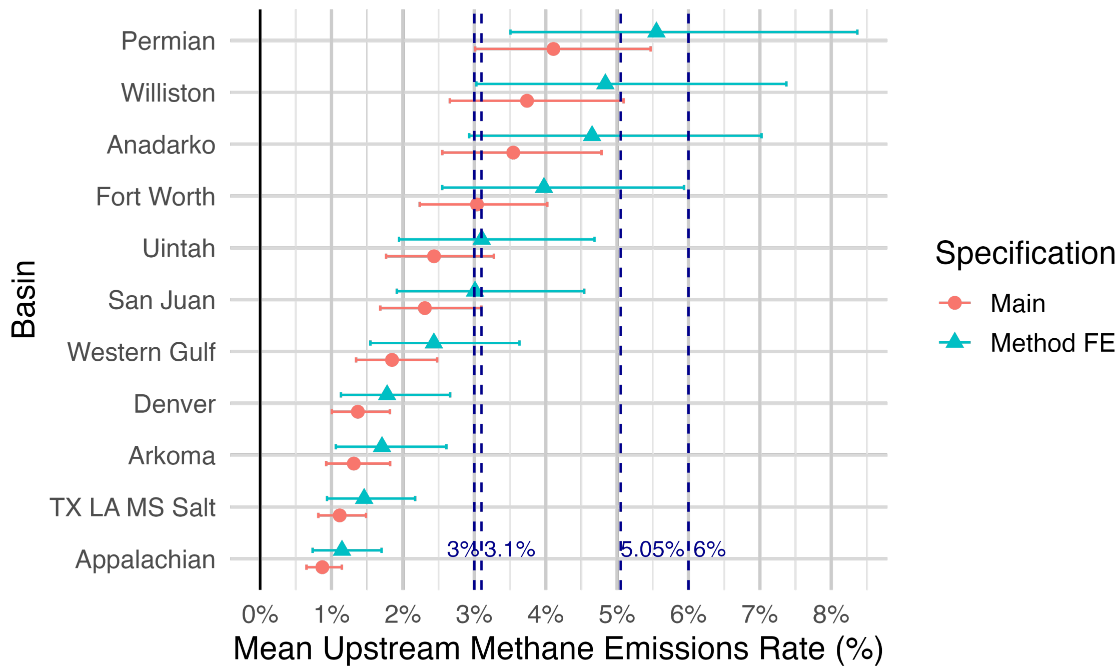

Figure A2. Posterior Coefficients for Alternate Specification: Method Fixed Effects. Coefficients from the primary model with method as a random effect are in red circles, whereas those from this alternate model are shown in blue triangles.

In the second alternative model specification, I simplify to a two-layer hierarchical model, dropping the study-level random effect. As before, the motivation here is to test alternative specifications to account for the possibility that there are not enough data points to estimate study-level heterogeneity. The effect of this change is to compress credible intervals, and largely leave point estimates unchanged except for the Uintah basin, where the estimate increases from approximately 2.5% in the primary specification, to approximately 4.5% in this alternate specification, and for the Permian basin, where the estimate decreases from approximately 4.1% in the primary specification, to approximately 2.8% in this alternate specification. Results are shown in Figure A3.

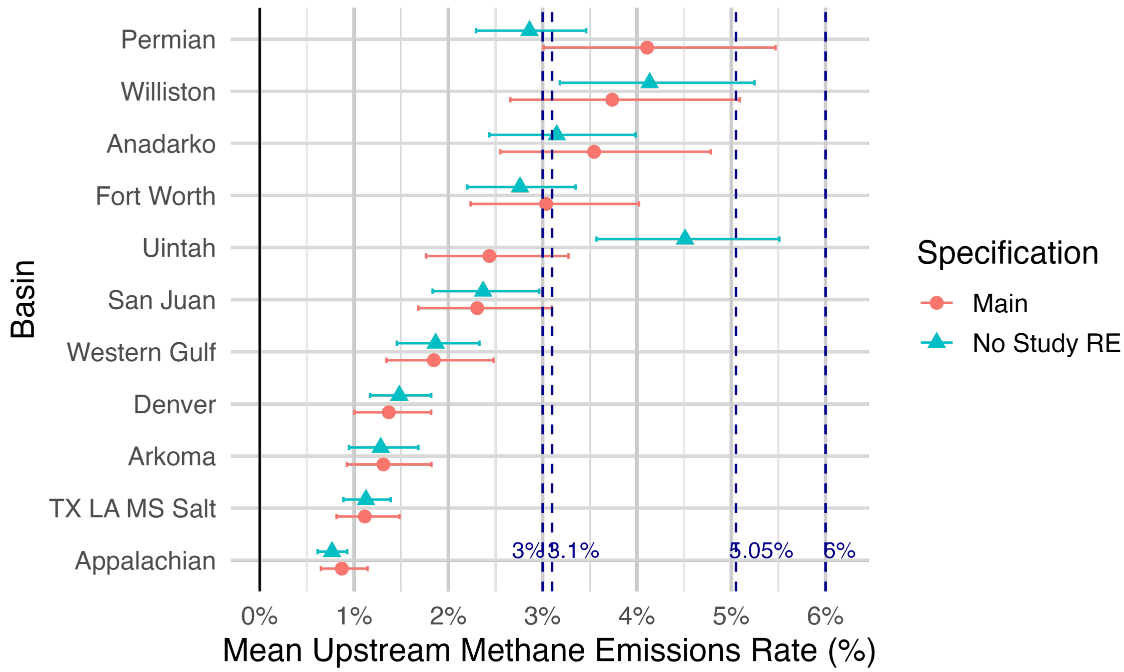

Figure A3. Posterior Coefficients for Alternate Specification: No Study-Level Random Effects. Coefficients from the primary model with method as a random effect are in red circles, whereas those from this alternate model are shown in blue triangles.

In the third variation, I test an alternative prior that is substantially less informative than the primary model. Here, I use a uniform distribution on the range 0%-10%. (To enable the log transformation, I choose the lower end of the range as 10^{-6}.) This change has no noticeable effect on the point estimates of the posterior, but it does (as expected) substantially widen the credible intervals. The Permian, Anadarko, and Williston basins may exceed the 5.05% breakeven rate under this specification. Results are shown in Figure A4.

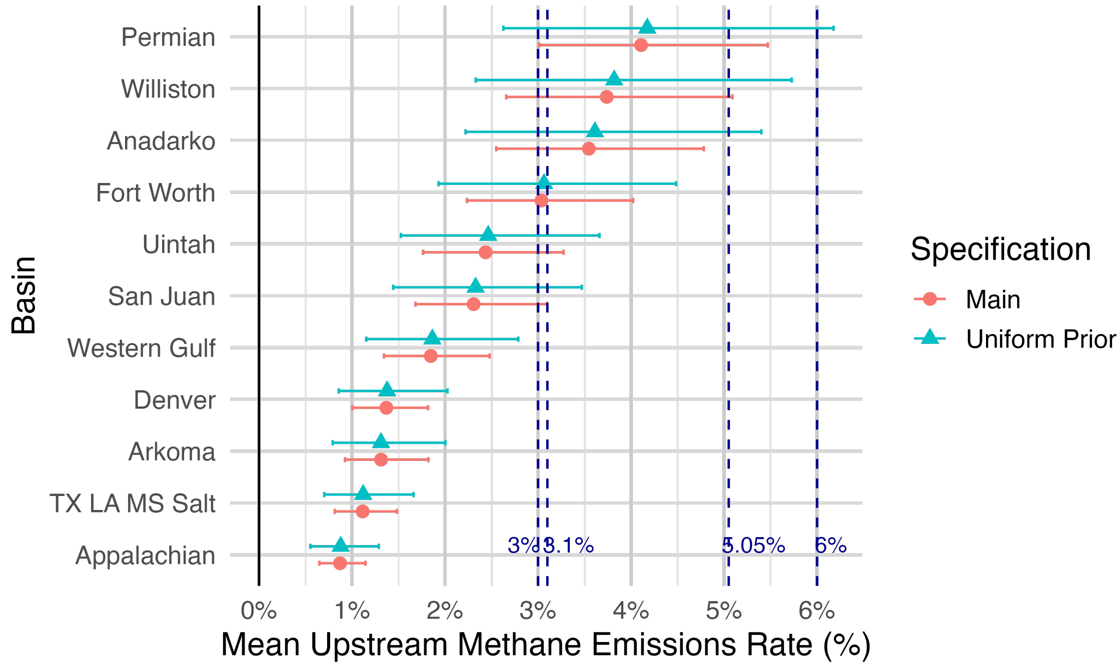

Figure A4. Posterior Coefficients for Alternate Prior: Uniform 0-10% Distribution. Coefficients from the primary model with method as a random effect are in red circles, whereas those from this alternate model are shown in blue triangles.