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Where Does the Marginal Methane Molecule Come From? Implications of LNG Exports for US Natural Gas Supply and Methane Emissions

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While the original submission of this article did not use artificial intelligence (AI) services, during revisions the author used the artificial intelligence service Claude Opus in preparing revisions to the code used to improve upon the paper's model, run sensitivity analyses, and build figures. The author reviewed and edited the output as needed and takes full responsibility for the content of the published article.

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Abstract

US exports of liquefied natural gas have surged over the past decade and are projected to more than double again by 2030 as more capacity is built. This has raised concerns about upward pressure on domestic energy prices as well as increased methane emissions from expanded oil and gas production. The magnitude of potential increases in natural gas prices depends on how much US supply is anticipated to respond, and impacts on methane emissions will depend on which oil and gas basins that supply will come from because methane leak rates vary dramatically across basins. Using a dataset on more than 1 million US oil and gas wells, I model the spatially heterogeneous supply responses to US export demand for both US natural gas and crude oil to estimate the impacts on domestic energy prices and the effective methane leak rates of marginal supply. Gas export demand mostly spurs marginal gas supply from Appalachia where methane leak rates are low, yielding effective methane leak rates more than 40% below the national average. Oil export demand mostly spurs production from the Permian Basin with effective leak rates nearly 3 times the national average. A gas export demand shock equivalent to roughly 1% of US supply drives larger gas price effects (+2.4% per billion cubic feet/day) than estimated in other studies, while oil export demand of similar magnitude has smaller impacts on oil prices (+0.9% per 100k barrels/day).

Keywords: liquefied natural gas, crude oil, methane emissions, energy prices

1. Introduction

US exports of oil and natural gas have boomed over the past decade. Fueled by the shale revolution, this boom started with the repeal of the crude oil export ban during the Obama administration and was subsequently bolstered by the rapid growth of liquefied natural gas (LNG) export terminals. While in 2015, the US imported 5 million barrels of per day (MMbbl/d) of crude oil and petroleum products on net, by the end of 2025 it was a net *exporter* to the tune of 3 MMbbl/d. The story is even more stark for natural gas. In 2023, a mere seven years after being a net importer of gas, the US surpassed Australia and Qatar as the world's largest LNG exporter, sending 12 billion cubic feet per day (bcf/d) of the fuel abroad. By 2025, that figure had risen to 15 bcf/d and could double further by 2029.[1] Yet the resulting increase in interdependency between US and global LNG markets presents both opportunities and challenges amid rising geopolitical tensions, ranging from the cutoff of Russian gas supplies during its invasion of Ukraine to the closing of the Strait of Hormuz amid the 2026 Iran conflict.

While crude oil markets have long been globally integrated, the difficulty of transporting natural gas overseas means gas markets historically have been regionally fragmented, partially insulating US consumers from supply disruptions abroad. But that is changing, as illustrated by the 2022 shutoff of Russian gas supplies to Europe during the war with Ukraine (Stock and Zaragoza-Watkins 2024). In August 2022, wholesale US natural gas prices soared to nearly $9 per million British thermal units (MMBtus), more than double its price the prior August ($4.07/MMbtu) and nearly quadruple its price a year before that ($2.30/MMBtu). US LNG exports directed to Europe helped to fill the supply gap there, but US energy prices surged, stoking inflation.

In the 2026 Iran conflict, approximately 20% of global oil supply was obstructed upon the closure of the Strait of Hormuz, sending crude oil prices up by 50% in the matter of days. At the same time, approximately 10 bcf/d of Qatari LNG production was shut down, knocking out about 20% of global LNG supply overnight. Yet while crude oil prices surged both globally and in the United States, US natural gas prices remained largely insulated from the global LNG price shock because US LNG export terminals were already operating at maximum capacity. Had more export capacity been available, US natural gas prices would likely have risen sharply as well.

While the dynamic for crude oil markets differs from that of gas, the search for replacement oil during the Iran conflict nevertheless began to stretch the limits of US crude oil export capacity,[2] leading the typical ~$2-5 per barrel discount in West Texas Intermediate (WTI) crude oil below Brent to explode to as large as $15-20 per

[1] https://www.eia.gov/todayinenergy/detail.php?id=66384
[2] https://finance.yahoo.com/news/us-crude-exports-test-limits-173120964.html

barrel.[3] Rumors that the Trump administration was considering restricting US crude oil exports to reduce domestic price pressure may have contributed to this dynamic, but the steep discounts persisted well after the administration later publicly rejected that option.[4] These events demonstrate that the effects of increased exports of US crude oil and LNG represent an important policy issue and even serve as key drivers of geopolitical events.

While the 2026 conflict in Iran has brought new attention to these issues, they are not new. In 2024, the Biden administration paused the approval of new permits for LNG export terminals, citing concerns about upward pressure on US energy prices and LNG's carbon footprint. However, that pause likely had limited practical impact because the Department of Energy (DOE) had already approved permits for LNG export capacity amounting to approximately 40% of current US gas production levels. By contrast, the second Trump administration has prioritized accelerating the permitting and construction of yet more LNG export capacity, which could lead to greater integration of global LNG markets but also greater domestic exposure to global gas price shocks.

Some proponents of advancing greater LNG exports argue that the US has abundant supplies to meet export demands without meaningfully raising prices (Yergin et al. 2024). But that conclusion hangs on an assumption that US oil and gas supply is highly elastic. On the other side of the debate are some environmentalists, who oppose expanding LNG exports out of concern about the US oil and gas industry's high rate of leaked methane, a highly potent greenhouse gas, which one study asserts makes LNG more carbon-intensive than coal (Howarth 2024). That study assumes high methane leak rates corresponding to the Permian Basin, the major oil play in west Texas and southeastern New Mexico that is the locus of much new oil drilling. Yet that assumption is only valid if the Permian Basin is the marginal source of gas supply. Methane leak rates are generally much lower in other US gas-producing regions compared to the Permian basin—up to an order of magnitude lower—suggesting those estimates may be overly pessimistic.

These arguments from both the industry's proponents and its critics ultimately rest on untested economic assumptions about the nature of US oil and gas supply. This paper assesses those assumptions by developing a spatially granular, econometrically calibrated model of US oil and gas supply based on the near universe of more than 1 million US oil and gas wells, greatly expanding on model advancements in past literature (Newell et al. 2019; Newell and Prest 2019; Prest 2022; Prest, Raimi, et al. 2024). I use this model to estimate the impacts of increasing oil and gas export demand on the spatially heterogeneous responses of US supply to those demand

[3] https://fred.stlouisfed.org/graph/?g=1UBWp
[4] https://www.politico.com/news/2026/03/19/white-house-crude-export-ban-oil-iran-00836300

pulls. This modeling also produces estimates of the increases in US crude oil and natural gas prices necessary to yield additional domestic production (and dampen domestic consumption) to meet export demand. Finally, I couple those spatially heterogeneous estimated supply responses with basin-level estimates of methane leak rates based on Sherwin et al. (2024) to estimate the weighted-average rates of methane leakage associated with the marginal sources of gas supply.

I find three key results. First, supply of both oil and gas from the Permian Basin responds strongly to oil prices (and hence oil demand shocks), whereas production in Appalachia, a major gas play, responds strongly to gas prices (and hence gas demand shocks). These two basins dominate the overall response of US gas supply to increased prices, together representing 59% of marginal gas supply in response to an exogenous increase in gas prices, holding oil prices constant, with Appalachia contributing 44 percentage points and the Permian contributing 15 percentage points. Moreover, an exogenous increase in gas export demand increases gas prices but modestly decreases oil prices due to induced coproduction of oil. This leads to an even larger response from Appalachia (57% of marginal supply) in response to gas demand relative to the Permian (2%) because of the latter's greater sensitivity to the reduction in oil prices, compared to the increase in gas prices. Thus, Appalachia dominates the marginal gas supply rising to meet LNG export demand.

The second finding follows from these dynamics: The marginal gas supply brought on in response to gas export demand has a methane emissions intensity (1.8% effective methane leak rate [95% range: 1.0-2.5%]) that is about 40% lower than the national average (3.1%) because of the disproportionate contribution of the low-leak Appalachian Basin. By contrast, the marginal gas supply induced by an increase in demand for US **oil** is nearly 3 times more methane-intensive (9.2% leak rate [95% range: 6.9-12.2%]) than average due to both a direct effect of a disproportionate contribution of marginal supply from high-leak Permian Basin and an indirect crowding out of production in low-leak Appalachia.

This crowding-out yields an effective leak rate that is higher than any basin's own leak rate (including the Permian) because high-leak Permian gas supply expands by more than 100% of incremental gas supply, while low-leak Appalachian gas supply contracts. As a result, the effective weighted-average leak rate puts more than 100% weight on the Permian basin's high leak rate, while Appalachia's low leak rate receives negative weight. This result mirrors the result in locational marginal emissions literature whereby a change in electricity demand shock can reshuffle generation away from low-emitting sources towards high-emitting ones, yielding marginal

emissions intensities greater than any individual generator (Rudkevich and Ruiz 2012), although the reshuffling mechanism differs here (coproduced goods, rather than grid congestion).[5]

These dynamics also highlight the consequential—rather than attributional—nature of the effective leak rates reported here. Relatedly, and as discussed in more detail in section 4.6, since my estimates are intended to correspond to the methane emissions caused by given exogenous shocks, I do not allocate the estimated methane losses to oil or gas production, which would introduce an unnecessary degree of arbitrariness. For both reasons, the reported leak rates correspond to consequential emissions accounting metrics and should not be compared to attributional accounting metrics or ones that are allocated between oil and gas production.

In terms of gross methane emissions, two gas export and oil export demand scenarios that are sized to be roughly similar percentages of US supply—at +1 Bcf/d gas export demand and +100k bbl/d oil export demand—also happen to produce similar amounts of methane emissions, despite yielding very different amounts of gas production. This result owes to the fact that while the amount of gas production induced by the +100k bbl/d increase in oil export demand is much smaller than the amount induced by a +1 Bcf/d increase in gas export demand (+0.1 Bcf/d versus +0.6 Bcf/d respectively), the much higher leak rate from oil demand (9.2% versus 1.8%) largely offsets this, thereby yielding qualitatively similar consequences for methane emissions.

Looking back historically, this result suggests that the 2015 repeal of the US crude oil export ban may have had larger, but less appreciated, consequences for driving US methane emissions than would halting approvals of LNG export approvals, as was considered by the Biden administration. Specifically, the model results suggest that the growth in US oil exports during 2015 to 2025 may have driven approximately twice as much methane emissions as did US LNG exports over the same period, with the former's emissions equivalent to those expected to be caused by 20-31 Bcf/d of gas export demand, which approximately corresponds to the range of future export capacity growth under consideration.

Third, I estimate that each +1 Bcf/d shift in LNG export demand (an amount that is slightly below 1% of US gas supply) increases wholesale US gas prices by approximately 2.4% while reducing crude oil prices by 0.6%. This effect is close to linear with respect to larger demand shifts. For context, approximately 11 Bcf/d of new LNG

[5] A simplified thought experiment demonstrates how this can happen. Suppose there are only two sources of gas supply, source A with a 1% leak rate and source B with a 5% leak rate. Suppose that because of a demand increase, B ramps up gas production by 2 and A ramps down by 1, yielding 1 unit of net increased gas production. Given the assumed leak rates, the total amount of methane leaked has increased by +2*5% – 1*1% = 0.10 – 0.01 = 0.09. This +0.09 unit increase in leaked methane is on a 1-unit net increase in gas production, implying an effective leak rate of 9%, similar to the actual result.

terminals were under construction as of 2024Q4, for which I estimate an increase in domestic natural gas prices of 30% alongside a 6.4% reduction in crude oil prices.

Three main caveats to these results are attributable to data limitations on the methane leakage rate estimates. First, the methane intensity estimates I use are based on Sherwin et al. (2024), whose study reflects nearly 1 million aerial site measurements taken across six major oil and gas producing US basins during 2016–21, including Appalachia and the Permian. However, some extrapolation to other basins is necessary. Second, improvements in methane capture could change those leak rates in the future, although the relaxation of methane regulations in the United States could slow those improvements. Third, because the most advanced sources of estimates of methane leak rates are based on the satellite and aerial flyover data, they cannot distinguish between methane emissions from new versus old infrastructure. As a result, the available data on methane leak rates represent basin-level averages across both old and new infrastructure, rather than leak rates from new wells specifically, which are likely lower. While this could suggest that the methane leak rates of marginal gas supply may be lower across the board than what basin-level average data suggest, it reinforces the key finding that the methane intensity of export-demand-driven marginal gas supply is likely to be relatively low.

Finally, because my model does not feature a representation of the global substitution patterns of LNG, my results do not speak fully to the global emissions effects of LNG, which could increase or decrease global carbon emissions depending on how much LNG use represents increased consumption of energy services and how much it substitutes for other fuels with potentially higher or lower carbon intensities. Abuin (2025) addresses this question, finding modest global emissions effects on net due to offsetting substitution patterns across global regions, a result that only serves to raise the importance of the impacts on domestic methane emissions.

Beyond contributing to the policy debate around the effects of US LNG exports, this paper also contributes to the broader literature on the economics of US oil and gas supply. In particular, I provide basin-level estimates of the elasticity of drilling with respect to oil and gas prices, new estimates of the elasticity of wells' initial productivity (IP) with respect to drilling activity, and time-varying own-price and cross-price elasticities of US oil and gas supply. The results show that the price elasticities of oil and gas supply are nuanced and vary over both time and space, implying temporally and regionally heterogeneous economic and environmental consequences of public policies and energy price shocks. The results I present can be used by researchers to go beyond the use of simplistic constant, static supply elasticity estimates.

2. Literature

This paper sits at the intersection of three literatures. The first is that of the economics of US oil and gas supply in the shale era, with a focus on supply elasticities. The second context is methane emissions from US oil and gas supply and the potential impacts of LNG exports on those emissions. The third regards recent analyses of the potential effects of LNG exports on US gas prices. I discuss each of these in turn.

2.1. Regional US Oil and Gas Supply Elasticities

While there is a broad literature on elasticities of oil and gas supply (see Prest et al. 2024 for a review of oil supply elasticities), much of that literature is not at the spatial or temporal scale necessary to address the question in this study, which requires estimating long-run equilibrium supply responses at the basin level or finer. By contrast, most estimates of oil and gas supply elasticities in the literature focus on short-run supply responses or are aggregated to a national or global scale (Hausman and Kellogg 2015; Balke and Brown 2018; Caldara et al. 2019; Kilian 2022). While some studies do consider specific US regions (Mason and Roberts 2018; Gilbert and Roberts 2020), they tend to be case studies of a single basin or a small number of regionally clustered basins, rather than nationally comprehensive estimates.

This paper is designed to fill that gap by improving the Dynamic Oil and Gas Market Analysis (DOGMA) model—a nationally comprehensive model of US oil and gas supply previously developed in a more spatially aggregated form in Prest (2022)—to account for regional heterogeneity in basin-level drilling elasticities and supply estimates. DOGMA has its roots in several papers in the economics literature of the shale era (Newell et al. 2019; Newell and Prest 2019; Prest 2022; Prest, Raimi, et al. 2024). Most relevant to this study are Prest (2022), who developed a nationally comprehensive model with US oil and gas supply aggregated into eight supply regions, and Prest et al. (2024), who developed a spatially granular model with 76 supply regions but include only five basins, all of which are in the American West. Those papers traded off regional granularity for nationwide comprehension or vice versa. The version of DOGMA developed in this paper extends the spatially granular model structure to the entire United States.

Prest (2022) models the market interactions between different sources of US oil and gas supply, in that case production on federally owned lands versus non–federally owned (i.e., private, state, and tribal) lands. This paper also analyzes those dynamics, but in a more granular fashion, which is necessary to account for basin-specific methane intensities. More details can be found in Section 4.

2.2. Methane Emissions from Oil and Gas Supply and LNG

Advances in remote sensing technology (both aerial and satellite) have sparked a wave of new research estimating methane emissions from US oil and gas infrastructure (Alvarez et al. 2018; Omara et al. 2018; Y. Zhang et al. 2020; Chen et al. 2022; Omara et al. 2022; Lu et al. 2023; Sherwin et al. 2024). That literature has repeatedly found that empirically estimated methane leak rates are much larger than the estimates in the US Environmental Protection Agency's two databases—the Greenhouse Gas Reporting Program (GHGRP) and the Greenhouse Gas Inventory (GHGI)—which are not based on direct empirical observations. For instance, Sherwin et al. (2024) combine approximately 1 million aerial site measurements across six regions, finding upstream/midstream methane leak rates ranging from 0.75% to 9.63% across regions, with a six-region weighted average of 2.95%, which they report was three times the corresponding GHGI estimate.

Two recent life-cycle analyses of the carbon intensity of LNG exports (Zhu et al. 2024; Howarth 2024) find that these upstream/midstream methane leak estimates are the single largest driver of LNG's total carbon footprint. In particular, in Howarth's central estimates, which assume a leak rate of 2.8% and a 20-year global warming potential (GWP20), upstream/midstream methane emissions are responsible for 36%–38% of LNG's total carbon footprint (and 18%–20% under GWP100) and are the primary driver of that paper's central finding that natural gas is 33% more carbon-intensive than coal. Thus, the appropriate methane leak rate is key to the question of whether LNG exports are deemed "worse than coal" from an emissions perspective.

While the Howarth study used a 2.8% leak rate to reflect the Permian Basin, a major December 2024 study from the Department of Energy (DOE 2024) used a central estimate of 0.56% for the national average "production through transmission network" leak rate from Khutal et al. (2024), who authored this report produced by the National Energy Technology Laboratory. The report relied on a combination of the GHGRP and GHGI data, which explains why the 0.56% leak rate is well below the empirical estimates from the literature.[6]

While the Howarth and the DOE studies use very different leak rates, neither of those estimates is informed by the economics of the oil and gas markets. Both studies assume constant leak rates, with Howarth using an estimate for the Permian Basin, assuming that Permian gas is the marginal supplier, whereas the DOE study's value is meant to reflect a national average. Neither approach is consistent with economic factors considered

[6] Despite this low assumed leak rate, the DOE study finds that in four out of the five scenarios, LNG exports increase global emissions (albeit by small amounts ranging from 0.002% to 0.05% of cumulative global GHG emissions in 2020–50), largely due to their model estimates, which suggest LNG would displace primarily lower-carbon energy internationally (including varying combinations of renewables, nuclear, and gas with carbon capture and storage), with displacement of higher-carbon coal playing a smaller role. Updating DOE's analysis to include leak rates more in line with the literature to values above 0.56% would presumably yield larger global emissions effects, but the magnitude would depend on assumed source marginal leak rate.

in this study. Indeed, my results suggest that very little gas supply expected to rise to meet gas export demand will come from the Permian, yielding a 1.8% marginal leak rate, which is about halfway between DOE's 0.56% and Howarth's 2.8%. This 1.8% central estimate further bears a 95% confidence interval of (1.0%, 2.5%) that easily rejects the values used by DOE and Howarth with a high degree of confidence.

The existing study that comes closest to addressing the question of the source of gas supply for LNG exports is that by Roman-White et al. (2024). Their study develops a "gas pathing algorithm" that combines information on gas purchase contracts held by a major LNG exporter and physical pipeline infrastructure to identify 138 potential pathways of natural gas production to two specific large LNG export terminals. While that approach may be appropriate for the purposes of attributional emissions accounting, such as supporting claims about the carbon intensity of a particular LNG exporter's supply chain, it does not alleviate concerns about the consequential emissions effects of LNG demand, which depend on outcomes in economic equilibrium. In particular, reshuffling of high- and low-leak gas supplies among gas purchasers could imply that attributional emissions (i.e., those from contracted supply chains) differ substantially from consequential ones (i.e., those caused in equilibrium across the market as a whole, which is the focus of this paper).

2.3. LNG Exports' Impact on Domestic Gas Prices

The DOE (2024) study uses a combination of the GCAM and NEMS models to estimate the impact of LNG exports on domestic gas prices, finding a central estimate of a 31% increase in domestic gas prices at Henry Hub in 2050 caused by a 32.6 Bcf/d increase in LNG exports (see DOE 2024, Table 10 and p. S-33). This implies an approximately 0.95% (=31%/32.6 Bcf/d) increase in Henry Hub prices per Bcf/d of exports.

A separate study was conducted by an independent arm of DOE (EIA 2023) as part of its 2023 Annual Energy Outlook, which also uses NEMS. The study estimates a price increase of 47% in response to about 32.9 Bcf/d increase in 2050. This also corresponds with a somewhat larger 1.4% (=47%/32.9 Bcf/d) increase per Bcf/d of exports. As discussed in Section 5, these estimates are substantially smaller than my results suggest due to much larger implicit gas supply elasticities in the DOE and EIA models.

Finally, a study by S&P Global (Yergin et al. 2024) estimates that an "extended halt" of LNG approvals that would reduce exports by approximately 5 Bcf/d would reduce US gas prices by $0.15/MMBtu on their baseline price of approximately $4/MMBtu, which corresponds to a price impact of about 0.75% per Bcf/d of exports.

3. Data

The main data underlying DOGMA is well-level data from Enverus on the near universe of oil and gas wells in the United States (Enverus 2024). The data include a cross-sectional dataset on well characteristics—including location (including latitude/longitude), basin, and dates of drilling and first production—and a well-by-month panel of oil and gas production from each well in the cross-sectional data. I supplement these data with WTI and Henry Hub price data from the Federal Reserve Economic Data system, which are converted into real 2023 prices using the Consumer Price Index for All Urban Consumers.[7] Future price scenarios and US oil and gas demand projections are taken from the International Energy Agency's *World Energy Outlook 2023* (WEO). GIS data from Esri is used to classify wells as on federal land (Esri 2018). I use EIA data on state-level gross and marketed gas production to convert projected gross withdrawals to marketed production when solving for price equilibria.[8] That completes the data necessary for the oil and gas production modeling.

The remaining data input is basin-level methane leak estimates, which are based on Sherwin et al. (2024) and provided by MiQ in the form of the open-source MiQ-Highwood Index (MiQ 2024). The MiQ dataset is based on the empirical measurements for the six basins in the study by Sherwin et al. (Appalachia, Permian, Denver-Julesburg, Fort Worth, Uinta, and San Joaquin). For other gas-focused basins (defined as basins with total gas-oil ratios above 100 thousand standard cubic feet per barrel), MiQ extrapolates the Sherwin et al. study's weighted-average empirical methane measurements of gas systems, and the measurements for petroleum systems are analogously extrapolated to oil-focused basins.

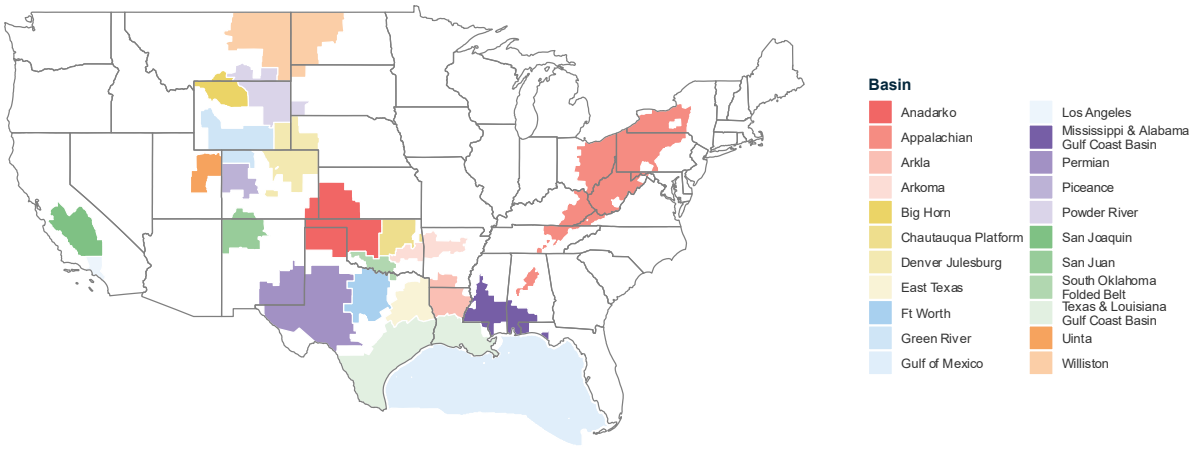
4. Methods

Ultimately, DOGMA projects county-level oil and gas production as a function of trajectories of oil and gas prices. While the core components of DOGMA have been documented in past research (Newell et al. 2019; Newell and Prest 2019; Prest 2022; Prest, Raimi, et al. 2024), this section provides a concise overview of the model with a focus on the extensions made in this paper. I categorize the dataset's approximately 1.2 million wells into 1,479 "well classes" that represent the permutation of US county and a federal/nonfederal land indicator. These well classes are nested under 24 basins (including one "Other" basin that aggregates 38 low-producing basins). Figure **1** shows a map of the key basins, and Appendix Figure A1 shows a map of the 1.2 million individual wells. I report results primarily at basin-level aggregates, but drilling and production are

[7] https://fred.stlouisfed.org/series/DCOILWTICO#0; https://fred.stlouisfed.org/series/PNGASUSUSDM#0; https://fred.stlouisfed.org/series/CPIAUCSL#0
[8] https://www.eia.gov/dnav/ng/ng_prod_sum_a_EPG0_VGM_mmcf_m.htm

nonetheless modeled at the well class level. While DOGMA models drilling and oil and gas production separately for each well class, in many cases well classes have inherited basin-level parameter estimates such as drilling elasticities.[9] Sections 4.1–4.4 provide more detail on the model of each stage.

Figure 1. Basin Map



Note: Alaska and "Other" basin categories are not shown for space and clarity.

For each well class, the oil and gas production process is divided into three stages: drilling wells, the time needed to complete them and begin production, and the trajectory of production from each well over time (the "decline curve"). Drilling is modeled using econometrically calibrated dynamic elasticities with respect to oil and gas prices, estimated using time-series distributed lag models separately for each basin. Past work has demonstrated that drilling investment is the key margin of price response for US oil and gas production (Newell et al. 2019; Newell and Prest 2019; Anderson et al. 2018). That literature has also found that the second and third stages are far less price responsive. Accordingly, I model the second stage—the time between the commencement of drilling and initial production—using their empirical distributions at the basin level. Similarly, I model the third stage—the decline curve of production from newly drilled wells—using empirical averages at the basin level, adjusted by an econometrically estimated relationship of initial production and drilling activity (discussed in section 4.3), which reflects diminishing resource quality as more wells are drilled.

[9] In principle, one could compute class-level estimates of certain parameters such as drilling elasticities or production curves, but this would introduce substantial noise in parameter estimates for classes with small numbers of wells in recent years.

4.1. Drilling

Historical time-series data have shown a clear relationship between drilling activity and oil and gas prices (Newell et al. 2019; Newell and Prest 2019; Prest 2022; Prest, Raimi, et al. 2024), with a modest lag. Time series of these variables are shown for each of the 24 basins in this paper in Appendix Figure A2, which illustrates that drilling activity ramps up when oil and gas prices do, thereby providing evidence for upward sloping drilling supply curves. Conceptually, upward sloping marginal costs of drilling can be driven by many factors, including heterogeneity in resource quality and endogenous rental costs of drilling rigs.[10] Heterogeneous resource quality pertains to the fact that some wells are anticipated to be more productive or cheaper to develop per unit of production by virtue of their geology. Thus, when prices rise, some previously unprofitable wells become economic to drill and complete. Heterogeneity in the gas-oil ratios of production both within and across basins further leads to heterogeneous responses to changes in oil versus gas prices, affecting the economics of gas plays disproportionately relative to oil plays.

I model this effect in reduced form by regressing the number of wells drilled in basin b in month t on oil and gas prices as follows:

$$\Delta \ln(d_{b,t}) = \sum_{\ell=0}^{12}[\eta_{b,\ell}^{oil}\Delta \ln(p_{t-\ell}^{oil}) + \eta_{b,\ell}^{gas}\Delta \ln(p_{t-\ell}^{gas})] + \lambda_{b,moy} + \varepsilon_{b,t}, \quad (1)$$

where p_t^{oil} and p_t^{gas} reflect the real (CPI-adjusted) prices of West Texas Intermediate crude oil and Henry Hub natural gas, respectively.[11] As in the related literature (e.g., Prest 2022; Prest, Raimi, and Whitlock 2024), 12 months of lags are included to reflect the observed delay in the response of drilling decisions to price fluctuations. The $\lambda_{b,moy}$ parameter is a month-of-year fixed effect to capture seasonality. The $\eta_{b,\ell}^{oil}$ and $\eta_{b,\ell}^{gas}$ parameters are the elasticities of drilling in basin b with respect to an ℓ-month lagged oil and gas price, respectively, and the long-run elasticities are $\overline{\eta_b^{oil}} = \sum_{\ell=0}^{12}\eta_{b,\ell}^{oil}$ and $\overline{\eta_b^{gas}} = \sum_{\ell=0}^{12}\eta_{b,\ell}^{gas}$, respectively.

[10] Anderson et al. (2018) estimate the daily rig rental rates covary with oil prices with an elasticity of 0.77, which, when coupled with persistent evidence both in that paper and this one that drilling also strongly covaries with oil prices, suggests marginal costs rise with drilling activity.

[11] While in principle one could consider modeling basin-specific gas prices, such as the Eastern Gas South pricing point for Appalachia, I do not do so for three reasons. First, in practice regional price movements are highly correlated with those at Henry Hub (see, e.g., https://www.eia.gov/naturalgas/weekly/archivenew_ngwu/2021/09_23/#itn-tabs-1) and hence would likely yield comparable results but inject unnecessary complexity into the model. Exceptions to this high degree of correlation typically occur in cases where local supply strongly affects local prices due to local oversupply such as in the Waha Pool, in which case using local prices would introduce strong endogeneity bias. Second, the use of Henry Hub prices implicitly builds into the elasticity estimates any frictions between local and Henry Hub prices that may attenuate the responsiveness of local drilling activity to changes in demand at the hub level. Third, the forward-looking scenarios from IEA include projections for Henry Hub prices but not local ones.

Equation (1) is estimated in first differences because of the failure to reject unit roots in oil and gas prices and in drilling activity for most (22 of 24) basins. Equation (1) is estimated jointly across all basins by seemingly unrelated regression (SUR), which permits the estimation of the joint uncertainty of all distributed lag terms across all 24 basins for use in a Monte Carlo analysis of the core outcomes of interest: effective leak rates and price impacts (see discussion in section 4.7), although I also show results under equation-by-equation ordinary least squares (OLS). As in past work (e.g., Prest 2022; Prest, Raimi, and Whitlock 2024), I do not instrument for the potential endogeneity of oil and gas prices to drilling activity for three reasons: i) the fact that drilling substantially precedes production mitigates this potential channel of endogeneity, ii) Wu-Hausman tests in the literature commonly find little empirical evidence of such endogeneity (Prest 2018; Newell and Prest 2019; Prest 2022) , and iii) the threat of weak instrument bias given the common difficulty of finding strong instruments for natural gas prices (Prest 2018, 2022; Hausman and Kellogg 2015) and the potential additional bias introduced by weak instruments (Bound et al. 1995).

Equation (1) is estimated over the period February 1992 to July 2023 (378 monthly observations) using Newey-West standard errors. As a sensitivity analysis, I also estimate equation (1) and the impacts on the key outcomes of interest on the restricted sample of 2010-2023 corresponding to the shale era.

Certain basins are pure gas plays and produce little to no oil. For example, in the Appalachian Basin, gas makes up 98% of oil and gas production on an energy basis. For the eight basins where gas makes up 90% or more of combined oil and gas production on an energy basis, I exclude the oil price from equation (1). Similarly, for the one basin where oil makes up more than 90% of production (the Los Angeles Basin), I exclude the gas price from equation (1). However, I also include a sensitivity analysis wherein I include all prices in all basins. As a final sensitivity analysis on the drilling elasticities, I also run the full model under a naïve sensitivity on the baseline in which all elasticity estimates are doubled.

For modeling future drilling, I apply the estimates of equation (1) to alternative International Energy Agency (IEA) scenarios for future oil and gas prices, focusing on the Stated Policies Scenario (STEPS), but in the appendix, I also show how the production projections vary under the Announced Pledges Scenario (APS) and Net Zero Emissions by 2050 Scenario (NZE), which feature lower oil and gas price trajectories. Appendix Figure A3 shows these price trajectories.

I begin with a baseline of current rates of drilling calculated separately by well class, denoted as $d_{j,0}$, as the average number of wells of that class drilled per month during the baseline period of 2022–23. Then I modify this baseline into the future dynamically using the $\eta_{b,\ell}^{oil}$ and $\eta_{b,\ell}^{gas}$ elasticities (using the same dynamic elasticity terms $\eta_{b,\ell}^{k}$ for all well classes j within basin b) over time applied to future pathways of p_t^{oil} and p_t^{gas} based on

the IEA price scenario. For any given price trajectory, this yields a path of wells drilled each month t for each well class j, which I denote as $d_{j,t}$.

4.2. Well Completion

Wells need to be drilled and completed before they are ready to produce oil and gas, and this process can take several months from the commencement of drilling. For example, the average well in the Permian Basin takes five months from drilling to production. I model this time lag between drilling activity and initial production using the empirical distribution of wells that entered production since 2012, by basin. These distributions are shown in Appendix Figure A4. As in Prest (2022), when computing these distributions I exclude wells with reported drill-to-production times exceeding 2 years onshore or 10 years offshore because investigations suggest these are likely data errors, although the paper's main results are not sensitive to this approach because the drill-to-production times primarily affect the time lag of the production response, rather than its overall level. Denoting the share of wells in basin b coming online ℓ months after drilling commenced as $s_{b,\ell}$, and applying it to the path of wells drilled in each class j (in basin b) over time $d_{j,t}$ yields the number of wells entering production in each class and month, denoted as $w_{j,t}$, as follows:

$$w_{j,t} = \sum_{\ell \geq 0} d_{j,t-\ell} s_{b,\ell}. \quad (2)$$

4.3. Production from Newly Drilled Wells

Next, I convert the trajectory of wells entering production for each newly drilled well in well class j, $w_{j,t}$, into their production of oil and gas over time, denoted as $Q_{j,t}^{oil,new}$ and $Q_{j,t}^{gas,new}$. This entails generating basin-level production profiles, or "decline curves," reflecting the pathways of oil and gas production from the typical well in each basin. This involves two steps. First, I compute the oil and gas decline curves for each basin by averaging the rates of oil and gas production across wells by the age of the well (in months) among all wells that entered production since 2012. This choice of a 2012 start year ensures enough history to compute at least 10 years' worth of decline curves. These decline curves are shown in Appendix Figure A5. However, because of the strong upward trend in initial production (IP) over the past decade or more, the inclusion of older wells in the calculation of the decline curves has the effect of understating the actual average IP of wells entering production today. Therefore, I rescale each basin's decline curves such that each curve's IP matches the corresponding average basin-level IP, denoted as $q_{b,0}^{k}$, among wells in each basin that entered production in the baseline years of 2022–23. The result is basin-level decline curves for each basin b, age τ, and product k, denoted as $q_{b,\tau}^{k}$. Total

production from newly drilled wells ($w_{j,t}$) from well class j (which is nested in basin b) in month t of product $k \in \{oil, gas\}$ is then

$$Q_{j,t}^{k,new} = \sum_{\tau=0}^{T} w_{j,t-\tau} q_{b,\tau}^{k}. \quad (3)$$

Production from these new wells can also be summarized at the basin ($Q_{b,t}^{k,new}$) or national ($Q_{t}^{k,new}$) level by summing across the appropriate well classes.

I also endogenize the overall production per well, $q_{b,\tau}^{k}$, to drilling activity to reflect the high-grading mechanism previously identified in the literature (Newell and Prest 2019; Gilbert and Roberts 2020). This reflects the fact that when drilling increases, average IP falls as lower-quality reservoirs are increasingly exploited. There are also other potentially relevant mechanisms through which changes in drilling activity may affect wells' productivity, such as behavioral responses like changes in drilled lateral length and proppant use, which we also wish to capture. To model these effects, I estimate the following equations for the IP of well i, denoted as $q_{i,0}^{k}$ for $k \in \{oil, gas\}$:

$$\ln\left(q_{i,0}^{k}\right) = \alpha_{b}^{k} + \beta^{k} \ln\left(w_{b,t_i}\right) + \theta^{k} t_i + \omega_{i,k}, \quad (4)$$

where w_{b,t_i} is the number of wells entering production in basin b in month t_i, as in equation (1), and t_i is well i's date of first production. α_{b}^{k} are basin IP fixed effects, and θ^{k} are time trends in IP.[12] Standard errors are two-way clustered on well and month of sample. The object of interest is β^{k}, which is the elasticity of IP of product k (oil or gas) with respect to within-basin contemporaneous wells entering production. β^{k} is anticipated to be negative, as increased drilling activity reduces average IP. While I do have data on lateral length, I do not include them in the regression as control variables because they represent a potential channel by which price-induced changes in drilling activity may affect IP, which is the goal of this estimation procedure; rather, we would desire any such drivers of the relationship of IP with contemporaneous drilling activity (whether observable or unobservable) to be reflected in the β^{k} coefficients, rather than controlled for.

I use these β^{k} elasticity values to adjust the baseline basin-level average production profiles as a function of simulated wells entering production, which in turn depends on prices per equations (1) and (2). This elasticity parameter has a meaningful impact on the overall elasticity of supply. Conceptually, the long-run elasticity of supply can be decomposed into the effects of price changes on wells entering production, $\overline{w}$, and the production

[12] Time trends are included to control for exogenous trends in technology and resource quality and knowledge. On one hand, resource quality may decline over time as the most productive known reserves are exhausted. On the other hand, companies tend to improve extraction technology and find better drilling locations over time (Agerton 2020). Regardless of which effect dominates, we want to control for these trends that may correlate with trends in drilling activity.

per well, denoted as $\overline{q^k}$, where the bars indicate long-run cumulative values of wells entering production and production per well.[13] Thus cumulative oil production can be written as $\overline{Q^{oil}} = \overline{w} \cdot \overline{q^{oil}}$. Given this notation, the long-run elasticity of supply for oil (and, by analogy, gas) can be written as follows:

$$\xi^{oil} = \frac{d\ ln(\overline{w} \cdot \overline{q^{oil}})}{d\ ln(p^{oil})} = \frac{d\ ln(\overline{w})}{d\ ln(p^{oil})} + \frac{d\ ln\left(\overline{q^{oil}}\right)}{d\ ln(p^{oil})} = \overline{\eta^{oil}} + \beta^{oil} \cdot \overline{\eta^{oil}} = \overline{\eta^{oil}}\left(1 + \beta^{oil}\right). \quad (5)$$

The first term, $d\ ln(\overline{w})/d\ ln(p^{oil}) = \overline{\eta^{oil}}$, follows from equation (1)[14]. The second term, $d\ ln\left(\overline{q^{oil}}\right)/d\ ln(p^{oil}) = \beta^{oil} \cdot \overline{\eta^{oil}}$, follows from the combination of equations (4) and (1). Intuitively, in the long run, a 1% increase in the price of oil increases the number of wells drilled by $\overline{\eta^{oil}}$%, but IP per well also changes by β^{oil}%. Presuming $\beta^{oil} < 0$, this mutes the supply response as $\overline{\eta^{oil}}$% more wells are drilled but each produces on average $|\beta^{oil}\%|$ less oil. While equation (5) illustrates how this high-grading effect mutes the supply response, it is nonetheless stylized because it pertains only to production from new wells and does not account for production from existing wells, which has been found in the literature to be effectively completely price inelastic (Newell et al. 2019; Newell and Prest 2019; Anderson et al. 2018). Thus equation (5) represents an upper bound on the overall supply elasticity.[15]

4.4. Production from Existing Wells

Sections 4.1–4.3 pertain to modeling production from newly drilled wells, but production is expected to continue from the approximately 600,000 wells reported as still producing in the data as of 2023–24. Past research has found that production from existing wells is almost perfectly inelastic to prices (e.g., Anderson et al. 2018; Newell, Prest, and Vissing 2019; Newell and Prest 2019) because operating costs are generally low and almost always below market prices, with rare exceptions for temporary shut-ins in cases of negative prices such as during the COVID epidemic. Therefore, for the still-producing wells, I project their production forward exogenously to 2050 using Arps curves, a standard method from petroleum engineering. This entails fitting the following pair of nonlinear equations (for $k \in \{oil, gas\}$) for each well and projecting it forward:

$$Q_{i,t}^k = \frac{c_i^k}{\left(1 + b_i^k a_i^k Well\ Age_{i,t}\right)^{1/b_i^k}} + \epsilon_{i,k,t}. \quad (6)$$

[13] Subscripts are omitted in this paragraph and the next because here I am considering long-run, steady-state values.
[14] By assumption all wells drilled eventually enter production because $\sum_{\ell \geq 0} s_{b,\ell} = 1$. Therefore, in the long run the oil price elasticity of wells drilled and wells entering production are both $\overline{\eta^{oil}}$, and similarly so for $\overline{\eta^{gas}}$.
[15] In the long run, production from inelastic existing wells would converge to zero, in which case equation (4) is a reasonable approximation.

The Arps curve parameters, including the initial flow rate c_i^k, initial decline rate a_i^k, and curvature b_i^k, are all estimated by nonlinear least squares separately for each of the approximately 600,000 existing producing wells. In a small number of cases, the nonlinear estimation fails to converge or produces parameters implying implausible exponential growth, rather than decline. In those cases, I impose an exogenous 3% monthly exponential decline from the last observed value, approximately in line with average decline rates. Wells are implicitly plugged and abandoned when their projected production goes to effectively zero.

Total production from existing wells in well class j is simply the sum across wells:

$$Q_{j,t}^{k,ex} = \sum_{i \in j} Q_{i,t}^{k}. \tag{7}$$

Production from existing wells can also be summarized at the basin ($Q_{b,t}^{k,ex}$) or national ($Q_t^{k,ex}$) level by summing across well classes. Total oil or gas production simply sums production from new (equation 3) and existing (equation 7) wells, yielding total US production of product k in month t: $Q_t^k = \sum_j Q_{j,t}^{k,new} + \sum_j Q_{j,t}^{k,ex}$.

Finally, two more adjustments must be made. First, as in Prest (2022), I find small discrepancies between total oil and gas production from wells in my dataset versus the national totals reported by EIA, likely because the Enverus data are not a 100% complete census. In particular, for 2022, EIA reports 3.0% more oil production and 3.8% more gas production (on a gross withdrawal basis) than the sum of production across wells in the dataset for that year. Therefore, I scale my total oil and gas production values up by factors of 1.030 and 1.038, respectively.

Second, the gas production in the data and hence all modeled gas production variables up to this point reflect gross withdrawals, not marketed production. While gross withdrawals are the appropriate metric for applying methane leak rates, marketed production is the appropriate metric when modeling market equilibria, discussed in Section 4.5. Approximately 90% of US gross withdrawals make it to market, but this fraction varies substantially by state. In most states, well over 90% of gas withdrawals is marketed, but in Alaska, that figure is only 10%, with the rest largely being reinjected, in part because of limited pipeline capacity from the Arctic Slope. Therefore, I convert gross gas withdrawals to marketed production by applying the historical 2022 marketed-to-gross production ratios from EIA on a state-by-state basis.[16] This primarily affects Alaska (10% marketed), Wyoming (80%), Montana (93%), and Texas (93%), although the paper's core results are not very sensitive to this approach.

[16] https://www.eia.gov/dnav/ng/ng_prod_sum_a_epg0_fgw_mmcf_a.htm

4.5. Modeling Demand Shocks

Sections 4.1–4.4 detailed how DOGMA models the effect of given oil and gas price trajectories on production at the class and county levels. This produces a baseline pathway of production, discussed in the next section. Against this backdrop, I conduct four types of experiments to assess different notions of marginal supply:

1. Exogenously shift US gas prices up by 1% in all periods, 2023–50.
2. Exogenously shift US oil prices up by 1% in all periods, 2023–50.
3. Exogenously shift demand for US gas up by a fixed amount in all periods, 2023–50.
4. Exogenously shift demand for US oil up by a fixed amount in all periods, 2023–50.

As noted previously, the central price scenario uses IEA's STEPS trajectories of oil and gas prices, so running the first two experiments simply entails slightly modifying those prices and rerunning DOGMA. These experiments also allow for computing both own-price and cross-price supply elasticities, both time-varying and cumulative.

I conduct the third and fourth experiments multiple times, varying the magnitude of the demand shift. These experiments are more complicated than the first two because they require modeling equilibrium prices. Solving for that equilibrium requires shifting oil or gas demand by some amount (e.g., +1 Bcf/d, which for reference is a bit less than 1% of US gas supply) and then asking what new oil and gas prices are necessary to clear the market, meaning freeing up an extra net supply (i.e., quantity supplied minus demanded) equal to the specified amount (e.g., +1 Bcf/d). Put simply, the solver seeks the increase in gas prices that is necessary to meet the specified increase in gas demand, induced both from higher US gas quantity supplied (from DOGMA) and lower local US gas consumption. For example, a specified +1 Bcf/d shift in demand could be met in theory by moving up along the supply curve by 0.6 Bcf/d and down along the (now shifted) demand curve by 0.4 Bcf/d, with the relative contributions determined by the implicit slopes of the two curves.

Since this requires modeling not only US oil and gas supply but also demand, I take the US oil and gas demand trajectory from the STEPS scenario. I assume that gas demand each year passes through the STEPS' annual price-quantity pairs with an elasticity of −0.23, which is the simple mean of long-run gas demand elasticity estimates from four studies (Newell and Raimi 2014; Arora 2014; Hausman and Kellogg 2015; Rubin and Auffhammer 2024). The approach for oil demand is analogous with a long-run oil demand elasticity of −0.33, which is the 21-study average from the survey in Prest et al. (2024).

There is an important caveat to the interpretation of the gas demand shock and oil demand shock scenarios. Because currently US LNG export capacity constraints are binding, the gas demand shock can be interpreted as the effect of increasing capacity—a current policy question. Oil export constraints, by contrast, are not always binding (although they were prior to the 2015 repeal of the export ban). This means that the increase in demand for US oil exports must be driven by global shocks to demand or supply (such as was seen in the 2026 Iran War)—not simply the relaxation of a physical oil export constraint, which does not always exist.

4.6. Incorporating Methane Leak Estimates

The previous sections complete the description of the oil and gas production modeling, which produces basin-level production projections. I couple this with basin-level estimates of methane leak rates based on Sherwin et al. (2024), provided in the form of the open-source MiQ-Highwood Index (MiQ 2024). Those estimates are already provided at the basin level, but the mapping to the basins in DOGMA is not perfect and requires a few modifications. First, there are two DOGMA basins that each map onto three distinct subbasins in the MiQ data: Appalachia and Fort Worth. For the Appalachian Basin in DOGMA, I take the gas production weighted average leak rate from the three relevant subbasins in MiQ: Appalachian Basin – Pennsylvania (0.75% leak rate, 44% of Appalachian production), Appalachian Basin (Utica) (4.62% leak rate, 3% of Appalachian production), and Appalachian Basin – Other (0.97% leak rate, 53% of Appalachian production). This yields a weighted average Appalachian leak rate of 0.98%. I conduct a similar exercise for the Fort Worth Basin, yielding a 3.1% weighted average leak rate. Finally, there are five basins in the Enverus data that are not in the MiQ data: the offshore Gulf of Mexico (<2% of marginal gas supply), Arctic Slope (also <2%), Los Angeles Basin (<0.01%), Big Horn (<0.01%), and my Other basin category (<0.4%). For these, I use the national average methane leak rate from the MiQ data of 2.7%, although this has little effect on the key results because those five basins collectively represent less than 4% of marginal gross gas supply.

Finally, it is important to emphasize that all leak rates reported in this paper correspond to the “unallocated” leak rates in the MiQ data, meaning the percentages represent methane emissions as a percentage of total gas production. This is in line with the values reported in Sherwin et al. (2024). However, an alternative approach would be to use only the portion of the leak rates “allocated” to the gas production, with the remaining emissions attributed to oil production on some basis (e.g., on energy share). I do not allocate leak rate estimates for several reasons. First, emissions allocation is essentially a joint cost allocation problem, and any such cost allocation method (whether on an energy basis or some other basis) ultimately contains some degree of arbitrariness (Lanen et al. 2019). Second, I am seeking to model “consequential” emissions rates—that is, the change in

methane emissions caused by given exogenous shocks, and the total emissions caused by such a shock will not depend on whether one decides to assign partial responsibility to one product versus another.

To see why, consider a thought experiment where an exogenous shift in export demand causes 100 units of additional gas production, and 3% of it is emitted to the atmosphere. The effect on methane emissions is clearly +3 units of methane. It does not matter for this conclusion whether the increased gas demand also caused 50 units of additional oil production and we were to allocate the 3 units in proportion to their supply shares (i.e., as 2 units to gas and 1 unit to the oil).[17] In that scenario, a complete accounting of methane emissions would require tracking the contributions of each product, which in either case depends on the full amount emitted, which here is 3 units. Focusing on the gas-allocated share, by contrast, would ignore the share of true emissions attributed to oil.

An important caveat is that because the most advanced sources of estimates of methane leak rates are based on the satellites and aerial flyover data, they cannot distinguish between methane emissions from new versus old infrastructure. As a result, the available data on methane leak rates represent basin-level averages, rather than leak rates from new wells specifically. While I am not aware of any data available on comprehensive, basin-level data on leak rates from new wells, it is likely that newly developed wells exhibit lower leak rates than their basin-level averages. While this could suggest that the methane leak rates of marginal gas supply may be lower than what basin-level average data suggest, it is unlikely to change the qualitative findings presented in the next section that the methane intensity of export-demand-driven marginal gas supply is relatively low. Lacking a clear quantitative basis for this point, I conduct a simple sensitivity analysis in which I haircut basin-level leak rates by assumed factors of 0.75x, 0.50x, and 0.25x, for Appalachia, Permian, or both, and report the resulting marginal effective leak rates. I also compare the main results based on methane leak rate estimates from Sherwin et al. (2024) to those from new satellite-based estimates of basin-level leak rates (Estrada et al. 2026).

4.7 Representing Uncertainty

I use Monte Carlo analyses to propagate uncertainty in key estimated parameters downstream into the model's outcomes of interest: effective methane leak rates and price impacts. Those outcomes are most affected by the cumulative supply elasticities, which depend primarily on the drilling elasticities $\eta^{k}_{b,\ell}$ and the IP elasticities β^{k} for $k \in \{oil, gas\}$. Thus, I sample from the distributions of those two sets of parameters: all drilling elasticity parameters ($\eta^{k}_{b,\ell}$, accounting for correlations across basins, lags, and oil versus gas price responses) and

[17] In fact, in that scenario, the combustion of that additional induced oil would lead to further overall emissions that would need to be accounted for in any comprehensive analysis of the emissions implications of the increased gas demand.

uncertainty in the IP coefficients (β^k). For each draw of parameters, I re-solve both the baseline supply trajectory and the perturbed scenarios with the incremental demand shocks.

Finally, I conduct a sensitivity analysis representing potential future constraints on pipeline takeaway capacity from Appalachia, which is a key driver of the results. While building a pipeline network is beyond the scope of this paper, I conduct a simple sensitivity analysis in which I cap Appalachia gas production at either 35 Bcf/d (slightly above current levels, consistent with no new pipelines) or 42 Bcf/d (consistent with only the currently planned ~7 Bcf/d of pipelines currently in development).[18]

5. Results

5.1. Drilling Elasticities

Figure **2** shows the estimates of the long-run basin-level drilling elasticities from equation (1). The oil-price elasticities $\overline{\eta_b^{oil}}$ are shown in the top panel, and the gas-price elasticities $\overline{\eta_b^{gas}}$ are in the bottom panel. In addition, the point estimates are accompanied by +/– 1.65 standard errors, consistent with a one-sided 95% confidence test. The estimates are broadly in line with expectations. All but three of the 39 point estimates are positive, reflecting drilling activity increasing when oil and gas prices rise. Two basins feature relatively small negative but insignificant point estimates for the long-run oil price elasticity—-0.18 (SE=1.15) for Big Horn basin and -0.04 (SE=0.49) for the Gulf of Mexico—while the Williston basin has a small and insignificant gas price elasticity of -0.04 (SE=0.47).

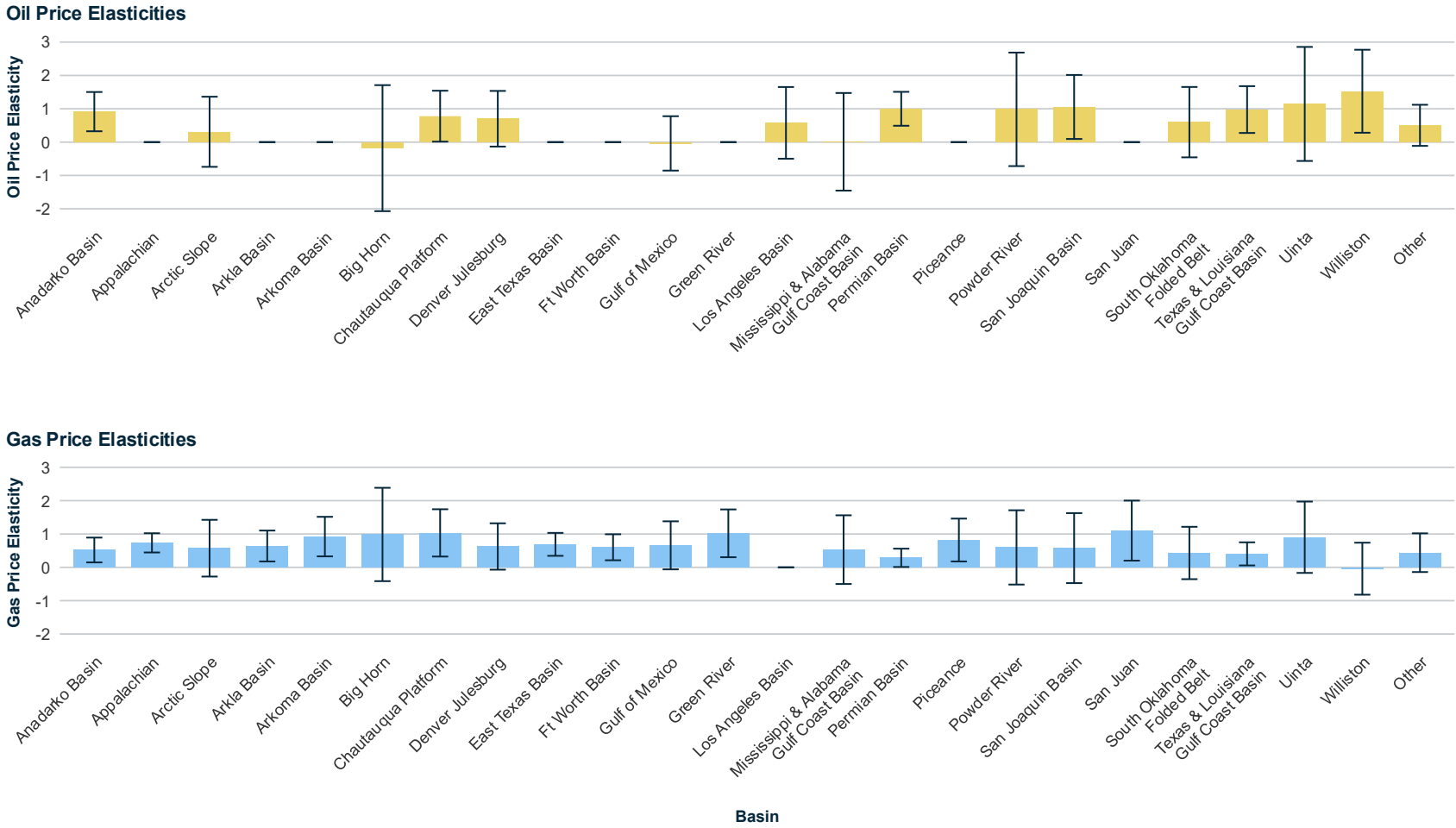
While Figure **2** shows elasticities for 24 basins, not all are equally important to this paper's key results because some basins are larger producers than others. As of 2022, the Appalachian and Permian basins together represented approximately half of US production of both natural gas and crude oil. Further, since those regions are the focus of the industry's recent and projected development, their roles are likely to grow even more important in the future. Therefore, those two basins' relative elasticities matter substantially more for the results than those for other regions and merit special attention. The Permian Basin's oil price elasticity is substantial and statistically significant at 1.00 (SE = 0.31), and its gas price elasticity is a modest and insignificant 0.29 (SE = 0.17). By contrast, Appalachia features a significant gas price elasticity of 0.73 (SE = 0.17). Appalachia's gas price elasticity of 0.73 is significantly larger than the Permian's 0.29 value at p=0.03. This result is robust to the three alternative elasticity estimation approaches, which yield p-values ranging between 0.01 and 0.04.

[18] https://www.mckinsey.com/industries/oil-and-gas/our-insights/the-infrastructure-imperative-who-benefits-from-pipeline-expansion#/

As noted in Section 4.1, Appalachia is one of the eight basins with very little oil production where oil prices are excluded from equation (1), and hence the oil price elasticity of zero shown in Figure 2 is a consequence of that assumption. Including the oil price in the regression for Appalachia yields a small negative and insignificant long-run oil price elasticity of −0.11 (SE = 0.36) and slightly increases the gas price elasticity to 0.84 (SE = 0.23), confirming the lack of an oil price response in that basin.[19] The elasticities in Figure 2 reveal that drilling elasticities vary substantially across regions, with oil plays responding disproportionately to oil prices and gas plays responding more to gas prices. While this finding comports with intuition, it also highlights that researchers should be careful not to simply extrapolate elasticities estimated in one region or case study to other plays where they are unlikely to be applicable.

[19] While this result might suggest simply retaining the oil price even in gas plays, including the oil price leads to implausible results in a few other gas plays. In San Juan Basin, including the oil price yields an implausibly large oil price elasticity estimate of 1.90 (SE = 1.13)—larger than in any other basin although San Juan is primarily a gas play (92% gas)—while dramatically changing the gas price elasticity from 1.10 (SE = 0.55) to 0.40 (SE = 0.76). This pattern of statistics suggests that some idiosyncrasy in the San Juan drilling time series is combining with the collinearity of oil and gas prices to load on the *a priori* "wrong" variable, which is why I drop the oil prices for those basins. However, the sensitivity analysis shown in section 5.7 shows that the paper's core results are robust to including both prices in all basins.

Figure 2. Long-Run Drilling Elasticities with Respect to WTI Crude Oil Prices (top panel) and Henry Hub Gas Prices (bottom)



Note: Error bars represent +/– 1.65 standard errors, consistent with a one-sided 95% confidence test. For basins with less than 10% of supply from oil (gas), the oil (gas) price is excluded from the regression and shown as zero.

Appendix Figure A6 compares the results from Figure **2** to those from the three alternative approaches to estimating these drilling elasticities: OLS (instead of SUR) on the full Feb-1992 to July-2023 window, SUR on the 2010-2023 window, and SUR on the full sample but including both oil and gas prices in all basins. Point estimates are largely consistent and the confidence intervals generally overlap across methods, with the exception of a small number of basins where point estimates and standard errors are both larger under the restricted 2010-2023 window (most notably Powder River basin). The results are otherwise robust for all important basins. The estimates for the key regions of Appalachia and the Permian are very similar. The gas price elasticity for Appalachia under the four {SUR, OLS, SUR 2010-2023, and SUR both prices} approaches are {0.73, 0.73, 0.92, 0.84} respectively with overlapping confidence intervals. While the standard error increases from 0.17 to 0.30 in the restricted 2010-2023 sample, the estimate remains statistically significant under all four approaches. In the Permian, the estimated oil price elasticity under the four approaches are {1.00, 1.13, 1.10, 1.13} again with overlapping confidence intervals and consistent statistical significance.

Quantitatively, these elasticity estimates are mostly in a similar range to those found in Prest (2022), where they can be most easily compared. For example, the onshore oil drilling elasticity estimate with respect to oil prices was 1.24 in Prest (2022), which is similar to this paper's estimate for the Permian Basin (1.0). Similarly, the onshore gas drilling elasticity with respect to gas prices was 0.63 in Prest (2022), which is similar to this paper's estimates of 0.73 and 0.64 for the top two gas-producing basins, Appalachian and Arkla Basins, respectively (where Arkla includes the Haynesville Shale). The biggest differences in the elasticities between Prest (2022) and this paper correspond to offshore drilling, which were estimated with the least precision in that study. The improved granularity of offshore basins and additional time series data in this paper suggest the offshore estimates included here represent an improvement on those from Prest (2022).

5.2. Elasticities of Initial Productivity

The estimated initial productivity elasticities, β^{oil} and β^{gas} from equation (4), are shown in Table **1**. The results imply elasticities of IP with respect to basin-level drilling activity of approximately −0.3 for oil IP and −0.4 for gas IP, both of which are significant at the 1% level. These suggest that for a 10% increase in local drilling, we would expect an average 3% reduction in oil IP and 4% reduction in gas IP.

Table 1. Initial Productivity Elasticities with Respect to Drilling

	Dependent variable	
	Log oil IP ($\ln(q_{i,0}^{oil})$)	Log gas IP ($\ln(q_{i,0}^{gas})$)
Variable	(1)	(2)
Log wells drilled ($\ln(w_{b,t_i})$)	−0.282***	−0.414***
	(0.067)	(0.115)
First production date (t_i)	0.0002***	0.0002***
	(0.00005)	(0.00003)
Observations	601,619	820,110
R^2	0.368	0.327

Note: *** p < 0.01

5.3. Production Pathways

Figure 3 shows the time paths of basin-level production of oil (top row) and marketed gas (bottom row). The three columns represent production from existing wells ($Q_{b,t}^{k,ex}$), new wells ($Q_{b,t}^{k,new}$), and total wells (their sum, $Q_{b,t}^{k}$). The Permian Basin (in purple) dominates oil supply in the recent past and in the future, followed by the Gulf of Mexico (light blue), Williston (orange), Texas & Louisiana Gulf Coast (light green), and Arctic Slope (light red), which together account for 87% of US oil production in 2050. By contrast, Appalachia (red) dominates gas supply in the recent past and future, followed by an increasing role for the Permian (purple) over time, supported by contributions from Texas & Louisiana Gulf Coast (light green), Arkla (pink; includes the Haynesville Shale), and Anadarko (dark red at top). Those five basins contribute 79% of gas production in 2050. Appendix Figures A8 and A9 show production pathways under lower APS and NZE oil and gas price scenarios, which feature roughly flat production and production declines, respectively.

Since I use the IEA's STEPS price scenarios, a comparison with the US oil and gas production projections in STEPS may be of interest. IEA does not present a distinct US crude oil production time series, making an apples-to-apples comparison difficult. However, it does report US tight oil projections (a subset of total US crude oil) in STEPS rising from 7.5 million barrels per day (MMbbl/d) in 2022 to about 9.5 MMbbl/d in 2030, before peaking and declining to 8.5 MMbbl/d in 2050 (see IEA 2023, 132). IEA also reports US gas supply growing by 90 billion cubic meters/year (about 9 Bcf/d) through 2030 before peaking and declining by 400 bcm (about 40 Bcf/d) through 2050 (see IEA 2023, 138), driven by declining projected US gas demand. In both cases, STEPS envisions

peak oil and gas production around 2030, likely driven by its assumptions around global decarbonization efforts. By contrast, my model projects that under STEPS oil and gas prices, US production is likely to continue to rise through the modeling window.

Figure 3. Projected US Oil and Marketed Gas Production from Existing Wells, New Wells, and Combined, under the STEPS Price Scenario



Notes: The five basins contributing the most to oil supply in 2050 are, in order, the Permian (purple), Gulf of Mexico (light blue), Williston (orange at bottom), Texas & Louisiana Gulf Coast (light green), and Arctic Slope (light red), which collectively account for 87% of oil production that year. The five basins contributing the most to gas supply in 2050 are Appalachia (red), Permian (purple), Texas & Louisiana Gulf Coast (light green), Arkla (pink), and Anadarko (dark red at top), which collectively account for 79% of gas production that year.

5.4. US Total Oil and Gas Supply Elasticities

As shown in equation (5) in the methods section, the long-run own-price elasticity of supply for product k can be approximated as $\overline{\eta^k}(1+\beta^k)$. While Figure 1 shows basin-specific drilling elasticity values, $\overline{\eta_b^k}$, Table **2** shows effective cumulative and long-run US-wide oil and gas supply elasticities, both own-price and cross-price. The cumulative (i.e., 2023–50 average) own-price elasticities are 0.53 for oil (95% range: 0.25-0.81) and 0.24 for gas

(95% range 0.14-0.39), which are computed by calculating the total response of total oil or gas production over 2023–50 in response to an assumed permanent 1% increase in crude oil or Henry Hub gas prices. In a sensitivity analysis, I turn off the high-grading effect by not applying the IP elasticities from Table **1**. This increases the cumulative supply elasticities to 0.76 and 0.42 respectively, since only the drilling response, and not endogenously declining IP, contributes to the supply change. These results closely align with the formula's approximation: $0.76(1-0.28)=0.55\approx0.53$ for oil and $0.40(1-0.41)=0.25\approx0.24$ for gas. Returning to Table **2**, the cross-price elasticities are small, at 0.21 (oil to gas prices) and 0.22 (gas to oil prices). Perhaps surprisingly, gas supply's cross-price elasticity is similar in size (0.22) to its own-price elasticity (0.24), a result driven in large part by substantial gas production from the Permian, where drilling is relatively inelastic to gas prices (0.29) but highly elastic to oil prices (1.0), as seen in Figure **2**.

Table 2. Cumulative (2023–50) and Long-Run Own-Price and Cross-Price Supply Elasticities

	Price	
Product	WTI crude oil price (p^{oil})	Henry Hub gas price (p^{gas})
Cumulative (2023-2050)		
Oil supply (Q^{oil})	0.53 (0.25, 0.81)	0.21 (0.07, 0.36)
Gas supply (Q^{gas})	0.22 (0.11, 0.39)	0.24 (0.14, 0.39)
Long-run (2050)		
Oil supply (Q^{oil})	0.59 (0.27, 0.90)	0.24 (0.09, 0.43)
Gas supply (Q^{gas})	0.27 (0.13, 0.46)	0.28 (0.16, 0.46)

Note: 95% intervals shown in parentheses. Gas supply values correspond to marketed gas supply, but elasticities for gross withdrawals are very similar.

More generally, the small own-price elasticity of gas supply of 0.24 can be decomposed into three effects. First, a substantial portion of US gas supply is relatively inelastically supplied by the Permian Basin, where oil prices are the main driver. This results in a US-wide gas-production-weighted average drilling elasticity with respect to gas prices of approximately 0.5, which happens to be halfway between the drilling elasticities with respect to

gas prices for the Permian of 0.29 and the Appalachian of 0.73. Second, applying the 40% discount from the gas IP elasticity of −0.4 (per equation 5) yields a gas supply elasticity from new wells of approximately 0.3. Third, including the perfectly inelastic supply from existing wells dilutes the elasticity value further, yielding the 0.24 final value.

Table 2 also shows long-run elasticities, defined as the price response in December 2050 induced by the same permanent 1% increase in price oil or gas prices over the full 2023–50 window. These long-run elasticities are modestly larger (11%–19%) than the cumulative ones, reflecting the lagged nature of the supply response. More detail on the full time paths of elasticities, both with and without the high-grading effect, can be seen in Appendix Figure A7 and downloaded from the hyperlink provided there.

5.5. Effects of Exogenous Price Shocks

Figure 4 shows each basin's contribution to US oil (top) and gross gas (bottom) supply in four notions of that concept.[20] The first two bars are average supply shares, historically (for 2022, in brown) and simulated future (2023–50 average, in green). The other two bars are each basin's share of *marginal* supply in response to an exogenous 1% increase in WTI oil prices (dark blue) or Henry Hub gas prices (light blue).

Comparing the first pair of bars, representing averages, with the others reveals which basins punch above or below their weight. Considering the oil supply shares in the top panel, most notable is the Permian Basin, which accounted for 46% of US oil supply in 2022 and 53% of future supply (2023–50 average) but 63% of marginal oil supply in response to an increase in oil prices. This outsize marginal response owes to its above-average drilling elasticity with respect to oil prices (1.0). This effect is even more pronounced in the bottom panel, which shows gas supply shares. The Permian Basin contributed 18% of total US gas supply in 2022 and is anticipated to contribute 26% in the future, but it nonetheless provides 57% of marginal gas supply brought online by an exogenous increase in oil prices. By contrast, the Permian's relatively modest drilling elasticity with respect to gas prices (0.29) means it contributes disproportionately less to gas supply in response to gas prices (15% marginal versus 18% historical and 26% future). A similar pattern can be seen for the Texas & Louisiana Gulf Coast and Williston Basins.

Gas-focused basins like Appalachia, Arkla, and East Texas (the last two encompass the Haynesville Shale) exhibit the reverse pattern, contributing disproportionately to marginal supply in response to gas prices.

[20] All subsequent figures and tables show gas supply shares as a share of gross gas withdrawals, not marketed production, because that is the relevant metric to which to apply the methane leak rate estimates based on Sherwin et al. (2024). However, market equilibrium is always computed using marketed production.

Appalachia dominates here, contributing 30% of gas supply in 2022, 31% in the future, but 44% in response to gas prices. This effect is driven by Appalachia's relatively large drilling elasticity with respect to gas prices of 0.73. As a gas play, Appalachia's drilling elasticity with respect to oil prices is assumed to be zero, as discussed in Section 4. However, including oil prices in its drilling equation would serve only to reinforce the findings shown here because doing so modestly increases Appalachia's gas price elasticity from 0.73 (SE = 0.17) to 0.84 (SE = 0.23); while also yielding a negative, albeit insignificant, estimate for the oil price elasticity (–0.11, SE = 0.36).

The only anomalous result seen in Figure 4 is that the Gulf of Mexico is found to respond more to gas prices than to oil prices, driven by its small oil price elasticity but nontrivial gas price elasticity (see Figure 2). While this could reflect the fact that for much of the sample period underlying the estimation of the drilling elasticities (1992–2023), the Gulf of Mexico was primarily a gas play even though forward-looking development there is more oil focused, the elasticities estimated only on the 2010-2023 period also yield negative and insignificant oil price elasticities for the Gulf of Mexico (Figure A6).

Figure 4. Oil and Gas Supply Shares by Basin: Historical, Projected, and Marginal in Response to Exogenous WTI and Henry Hub Price Shocks



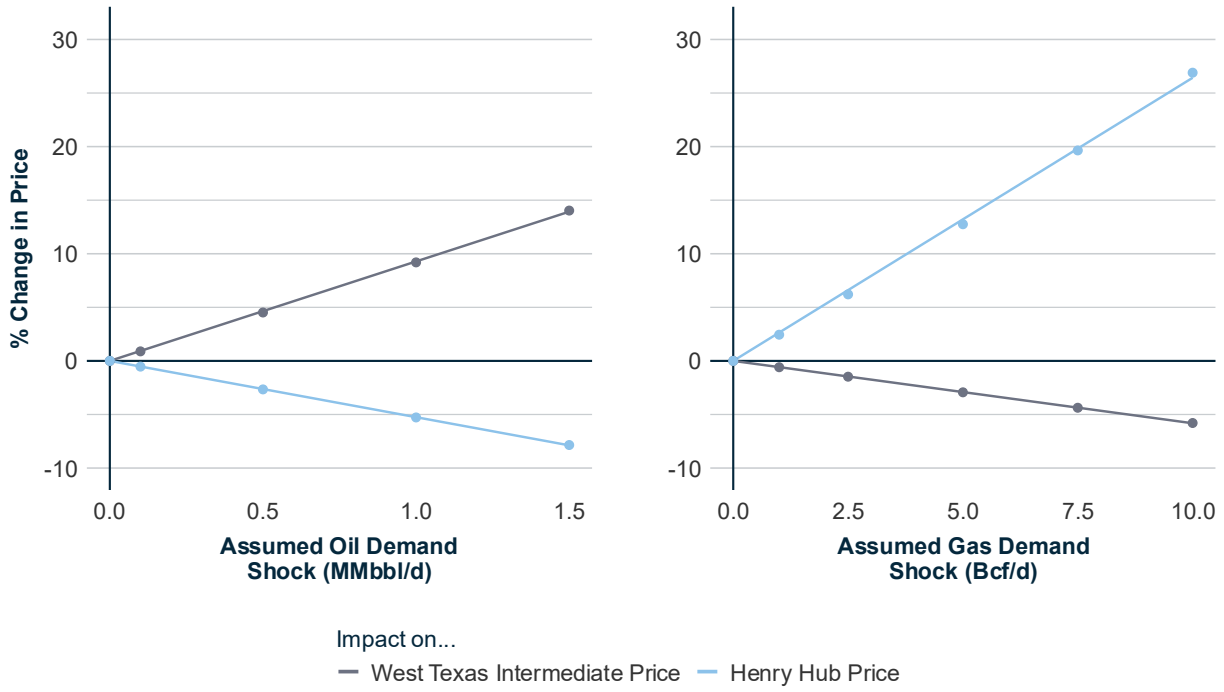
5.6. Effects of Exogenous Demand Shocks

Regarding the demand shock results, Figure 5 shows the price impacts from gas and oil demand shocks of a variety of magnitudes. I show results for gas demand shocks of 1, 2.5, 5, 7.5, and 10 Bcf/d (left panel) and for oil demand shocks of 0.1, 0.5, 1, and 1.5 MMbbl/d (right panel). These loosely range between 1% and 10% of US production levels of each product. As noted in section 4.5, an important caveat to the interpretation of these results is that currently US LNG exports are constrained by limited export capacity, while crude oil exports are not. Therefore, while the gas demand shock scenarios can be interpreted as the relaxation of current binding export constraints, the oil demand shock scenarios should be interpreted in today's economic context as an assumed increase in demand for US oil driven by global shocks to demand or supply (such as was seen in the 2026 Iran War).

The gas demand shocks increase Henry Hub prices by approximately 2.4% for each Bcf/d of demand shock, while the coproduced oil pushes oil prices down by about 0.6% per Bcf/d. The effect is approximately linear, hitting +27% for Henry Hub and –5.8% for WTI under the 10 Bcf/d shock. This linearity result owes to a combination of the log-log specifications of the equations for the response of wells drilled (equation 1) and production per well (equation 4), which together imply a supply elasticity that is approximately constant in price-quantity space (although the elasticity varies across time and basin). Those assumptions, coupled with assumed constant elasticities of demand for oil and gas, yield a linear price impact.

The results under the oil demand shock mirror those of the gas demand shocks. For each 100,000 bbl/d in oil demand shock (a bit less than 1% of US crude oil supply), oil prices increase by about 0.9%, while gas prices decline by about 0.5%. That the effects for oil are smaller than for gas is due to the larger overall estimated oil price elasticities of drilling (and hence oil and gas supply) with respect to oil prices versus gas prices (see Figure 2). This yields a flatter supply curve and hence less price response. The larger assumed elasticity of oil demand (–0.33) relative to gas demand (–0.23) further reinforces this effect.

Figure 5. Impacts of Exogenous Gas and Oil Demand Shocks on WTI and Henry Hub Prices



Note: The pairs of points along the *x*-axis each represent a single model run with an exogenous, permanent assumed shift in export demand in every period 2023–50, which must be met by some combination of higher cumulative US quantity supplied and lower quantity demanded. Demand is price responsive with elasticities of –0.33 for oil demand and –0.23 for gas demand. Best-fit lines are constructed using ordinary least squares, constrained to go through the point at the origin.

Figure 5 reveals an important distinction between a pure increase in gas prices and an increase in gas demand: cross-price effects. Increased gas demand stimulates oil coproduction, which puts downward pressure on oil prices. This thereby reduces drilling in basins with strong oil price responses like the Permian Basin. These cross-price effects mute the overall gas supply response from oil plays like the Permian, relative to what would be induced by a pure increase in gas prices. Similarly, increased oil demand stimulates gas coproduction, which puts downward pressure on drilling in gas plays and hence on their gas supply response.

This effect can be seen in Table 3, where columns (1) and (2) show each basin's drilling elasticities, (3) shows methane leak rates based on Sherwin et al. (2024), and (4–9) show gas supply shares under all six notions of that concept: (4) average historical; (5) average future; and marginal with respect to (6) Henry Hub prices, (7) gas demand, (8) WTI prices, and (9) oil demand. For space, Table 3 shows only the 11 largest gas-producing basins, although the weighted average

leak rates are computed using all 24 basins.[21] Appendix Table A1 shows the results for all 24 basins, and Appendix Table A2 shows the results for the share of oil supply contributed under each scenario.

Table 3. Basin-Level Drilling Elasticities, Methane Leak Rates, and Gas Supply Shares

				Gross gas supply share (%)					
	Drilling elasticity with respect to …			Average		Marginal in response to …			
Basin	Henry Hub prices	WTI prices	Methane leak rate (%)	Historical (2022)	Projected (2023–50)	+1% Henry Hub price	+1 Bcf/d gas demand	+1% WTI price	+100k bbl/d oil demand
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Appalachian	0.73	—	1.0%	30%	31%	44%	57%	0%	-79%
Permian	0.29	1.00	5.3%	18%	26%	15%	2%	57%	133%
Arkla	0.64	—	1.0%	9%	8%	11%	14%	0%	-19%
Texas & Louisiana Gulf Coast Basin	0.40	0.98	4.6%	7%	8%	7%	3%	17%	36%
Arctic Slope	0.57	0.31	2.7%	7%	3%	1%	2%	1%	-0.3%
Anadarko	0.52	0.91	4.6%	5%	4%	4%	3%	8%	15%
East Texas	0.69	—	4.6%	5%	5%	7%	9%	0%	-12%
Williston	-0.04	1.53	4.6%	3%	3%	-0.2%	-3%	9%	25%
Denver Julesburg	0.63	0.70	1.1%	3%	2%	3%	3%	3%	4%
Green River	1.02	—	4.6%	2%	1%	1%	1%	0%	-1%
Ft Worth	0.60	—	3.1%	2%	1%	1%	1%	0%	-1%
Weighted-average methane leak rate in column (3), using columns (4–9) as weights				**2.8%**	**3.1%**	**2.5%**	**1.8%**	**4.9%**	**9.2%**

Note: Basins are sorted in order of column (4), the 2022 gas supply share. Because of space constraints, only the 11 largest gas-producing basins are shown here, but the weighted average leak rates are computed using all 24 basins. The 11 basins shown here made up 90% of US gas supply (and 77% of oil supply) in 2022 and more than 90% of projected average and marginal gas supply. A version of this table including all 24 basins is included in the appendix. All shares correspond to shares of gross withdrawals, not marketed gas. This distinction is important primarily for the Arctic Slope, where only 10% of gross withdrawals make it to market, with most being reinjected, although it has negligible effects on the estimated leak rates because the Arctic Slope only amounts to 1-2% of marginal supply even in gross withdrawal terms.

[21] All gas supply share figures in Table 3 are expressed in terms of share of gross gas withdrawals, not marketed production, as gross withdrawals are the relevant variable for applying leak rates. This affects primarily the interpretation of the Arctic Slope row, which amounts to 1-2% of marginal gross withdrawals but only about 0.1-0.2% of marketed supply because in Alaska, about 90% of gross gas withdrawals are reinjected. This distinction has negligible effects on the estimated leak rates because the Arctic Slope is already a very small share of marginal supply even in gross withdrawal terms.

Appalachia contributes 57% of gas supply in response to gas demand, more than the 44% it would contribute in response to a pure increase in gas prices. Meanwhile, the Permian Basin contributes only 2% of marginal gas supply in response to gas demand, despite contributing 15% in response to a pure increase in gas prices. This result is driven by the relative size of the estimated drilling elasticities with respect to gas prices in Appalachia (0.73) versus the Permian (0.29), rather than their absolute values. This result is corroborated by the sensitivity analysis in the next section in which I double all elasticity estimates, which further augments this divergence in supply shares across these basins.

This disproportionate contribution of Appalachian gas supply relative to the Permian has important implications because the Permian Basin has among the highest estimated methane leak rates (5.3%) and Appalachia has the lowest (1.0%), suggesting that the marginal supply rising to meet export demand is likely to come disproportionately from low-leak Appalachia, not the Permian as is commonly assumed (Howarth 2024; Department of Energy 2024). The bottom row of Table **3**, in columns (4–9), shows the supply share–weighted average leak rate using each supply share concept. While the production-weighted average leak rates are 2.8% (historical) and 3.1% (future), the more appropriate *marginal* weighted averages are lower, at 2.5% (95% range: 1.7-3.2%) for a +1% gas price increase and 1.8% (95% range: 1.0-2.5%) for a +1 Bcf/d gas demand increase. This 1.8% value would be the appropriate value to use when modeling the upstream/midstream methane intensity of LNG exports, and it is nearly 40% smaller than the value of 2.8% used by Howarth (2024). In the sensitivity analysis in which all drilling elasticities are doubled, the gas supply response is further weighted towards Appalachia and away from the Permian, yielding an even lower weighted average leak rate of 1.5%.

On the other hand, Table **3** also suggests that gas supply induced by oil demand is likely to come disproportionately from the high-leak Permian Basin. In fact, the downward pressure on gas prices induced by increased oil demand both increases coproduced Permian gas and decreases Appalachian production, such that the Permian Basin contributes more than 100% of incremental gas supply induced by oil demand (see column [9]).

In other words, in response to an increase in oil demand, Permian gas crowds out Appalachian gas. This modeled result is consistent with recent observed trends in play-level gas production, where high oil prices have spurred associated gas production in the Permian, while gas production from gas plays has stagnated or declined.[22] The consequence of this crowding-out effect is that the weighted average leak rate of the incremental gas supply is a very high 9.2% (95% range: 6.9-12.2%).

In fact, this crowding-out effect causes the effective weighted-average leak rate to exceed that of any individual basin. A simplified thought experiment demonstrates how this can happen. Suppose there are only two sources of gas supply: source A with a 1% leak rate and source B with a 5% leak rate. Suppose that because of a demand increase, B ramps up

[22] https://www.eia.gov/todayinenergy/detail.php?id=63506

gas production by 2 and A ramps down by 1, yielding 1 unit of net increased gas production. Given the assumed leak rates, the total amount of methane leaked has increased by +2*5% – 1*1% = 0.10 – 0.01 = 0.09. This +0.09 unit increase in leaked methane is on a 1-unit net increase in gas production, implying an effective leak rate of 9%, similar to the actual result. While the actual calculation is more nuanced, this example captures the basic idea. The result is also similar in spirit to the result from the locational marginal emissions literature, where a marginal increase in electricity demand can reshuffle generation away from moderately emitting plants towards high-emitting ones, resulting in effective marginal emissions rates much larger than any individual plant's own rate (Rudkevich and Ruiz 2012).

In terms of gross methane emissions, both the +1 Bcf/d gas demand and +100k bbl/d oil demand scenarios—which are sized to be roughly similar percentages of US supply—also happen to produce similar amounts of methane emissions, despite yielding very different amounts of gas production. In particular, the +1 Bcf/d gas demand shock results in about 0.6 Bcf/d more US gas production,[23] which at a 1.8% leak rate implies about 0.073 MMt of methane emissions, assuming a 90% methane content.[24] By comparison, the 100k bbl/d oil export demand scenario induces about 0.1 Bcf/d of coproduced gas, which at a 9.2% leak rate implies a similar 0.061 MMt of methane emissions.[25]

Looking back historically, this result suggests that the 2015 repeal of the crude oil export ban may have had underappreciated implications that rival those expected to be driven by LNG exports. Table 4 shows a series of back-of-the-envelope calculations demonstrating this result. Each 1 MMbbl/d of oil export demand in my model induces about 1.0 Bcf/d of coproduced gas, which at a ~9% marginal leak rate implies about 0.62 million metric tons (MMt) of methane. As a back-of-the-envelope calculation, US crude oil exports have risen by about 2.3–3.6 MMbbl/d since 2014,[26] implying that this growth in US oil exports to date may have driven 1.4–2.3 MMt of methane emissions annually, equivalent to what would be caused by about 20–31 Bcf/d of gas exports. For context, US export capacity as of 2024Q4 was 14 Bcf/d, with a total of more than 40 Bcf/d approved to date by DOE.

As another point of comparison, the United States exported a total of 28 trillion cubic feet (Tcf) of LNG from 2015 to 2025. The cumulative methane emissions associated with that amount of gas production would be 9 MMt of methane at a leak rate of 1.8%. By contrast, during the same period, the United States exported 11 billion barrels of crude oil, which my model suggests induced about 11 Tcf of gas production with the far higher leak rate of 9.2%, implying 18 MMt of cumulative methane emissions, or twice the 9 MMt figure associated with historical US LNG exports. Table 4 presents these estimates alongside 95% confidence intervals accounting for uncertainty both in the magnitude of the supply

[23] The remaining 0.4 Bcf/d of export needs is met by lower domestic gas consumption.
[24] 0.073 MMt = (0.62 Bcf/d)×(365 days)×(1.8% leak rate)×(90% methane content)÷(48.7 Bcf/Mt).
[25] 0.061 MMt = (0.1 Bcf/d)×(365 days)×(9.2% leak rate)×(90% methane content)÷(48.7 Bcf/Mt).

[26] Crude oil exports in 2025 were 3.6 MMbbl/d higher than in 2014 and 2.3 MMbbl/d higher on average over 2015–25 (see https://www.eia.gov/dnav/pet/pet_move_exp_dc_NUS-Z00_mbblpd_a.htm).

response to export demand and in the leak rate due to its composition. While the central estimate is that cumulative historical oil exports are associated with 2x the methane emissions as historical LNG exports, the uncertainty range on this estimate is broad at (0.9x, 5.0x). Nevertheless, more than 95% of Monte Carlo draws yield a greater effect from historical US crude oil exports than from LNG.

Table 4. Comparison of Emissions Consequences of Historical Oil versus LNG Export Levels

	Point estimate	95% Range
Annual Methane Emissions (MMt/yr)		
per +1 MMbbl/day oil export demand	0.62	(0.34, 0.99)
per +1 Bcf/day gas export demand	0.073	(0.04, 0.11)
ratio	8.5x	(4.0x, 20x)
per +2.3 to +3.6 MMbbl/day crude oil exports	1.42 to 2.23	(0.79, 2.27) to (1.24, 3.56)
per +20 to +31 Bcf/day gas exports	1.46 to 2.26	(0.73, 2.11) to (1.12, 3.26)
Cumulative Methane Emissions 2015-2025 (MMt)		
per +11 Tcf induced coproduced gas from +11 billion barrels crude oil exports, at oil demand leak rate	18.0	(10.0, 28.8)
per +28 Tcf gas, at gas demand leak rate	9.0	(5.1, 12.8)
ratio	2.0x	(0.9x, 5.0x)

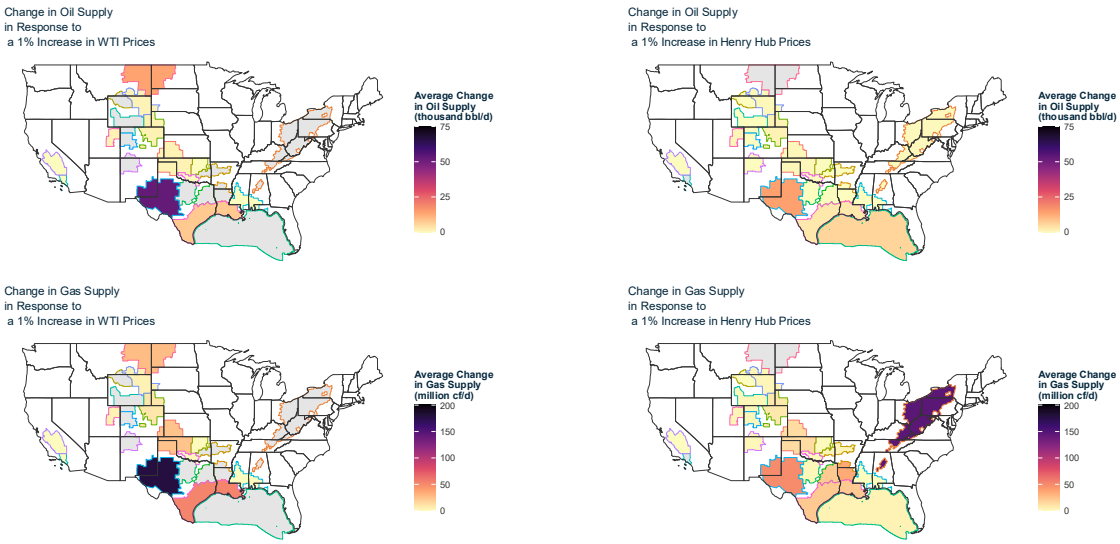
While the increase in gas prices shown in Figure 5 could in principle encourage operators to reduce their leak rates via the greater incentive to capture otherwise lost methane (Marks 2021), a back of the envelope calculation suggests such an effect is unlikely to have a meaningful impact on the weighted average leak rates in Table 3. The gas price changes in columns (6), (7), (8), and (9) range between +2.4% (column [7]) and -0.5% (column [9]). Marks (2021) estimates that a $1/MMBtu increase in Henry Hub gas prices is expected to reduce methane leak rates by about 0.23%, and this effect is found to be roughly linear. Applying this estimate to the price changes above, using $4/MMBtu as a baseline average gas price, yields changes in leak rates ranging between -0.02 and +0.005 percentage points, compared to the effective leak rates in the last row ranging between 1.8% and 9.2% respectively.[27]

A final caveat is that while the Sherwin et al. (2024) estimates include methane emissions from both upstream and midstream infrastructure, they only reflect methane emissions within each basin's borders and therefore do not include emissions from pipeline infrastructure between each basin and LNG export terminals, most of which are along the Gulf Coast in Texas and Louisiana. As a sensitivity analysis, I use the estimate from Zhang et al. (2026) of emissions of 4 $kgCO_2e$ (at the 100-year AR6 GWP) per MMCF per km transmitted, which translates to a percentage loss rate of 0.000785% per km, or about 0.785% loss per 1,000 km traveled. Then for each basin I compute the Haversine distance

[27] For example, in the +1 Bcf/d column (7), the estimated 2.4% increase on a $4/MMBtu average base gas price is approximately $0.10/MMBtu. Applying Marks' estimate to this value yields -0.23%/($/MMBtu)*$0.10/MMBtu ≈ -0.02%, which would barely move the estimated leak rate of 1.8%.

between the capacity-weighted mean latitude/longitude of existing US LNG export terminals (29.71°N, 93.01°W, in Cameron, LA, near the Venture Global LNG export terminal) and the production-weighted[28] average latitude and longitude of operating wells in each basin during the baseline years of 2022-2023. Multiplying this loss rate by the average distance to LNG terminals yields a transmission loss rate for each basin. However, this calculation should be interpreted as a sensitivity analysis only because these values may double count within-basin transmission losses already accounted for in the Sherwin et al. (2024) estimates. The resulting estimated transmission loss rates are 1.4% for Appalachia, 0.8% for the Permian, and 0.2% for Arkla, reflecting their relative proximities to LNG export infrastructure. Nationally, the resulting average well-through-transmission average leak rate rises from 3.1% to 4.1%, the leak rate estimate in response to gas export demand rises from 1.8% to 2.8%, and the leak rate in response to oil export demand rises from 9.2% to 9.8%. Thus, the relative leak rate finding is robust to including transmission emissions.

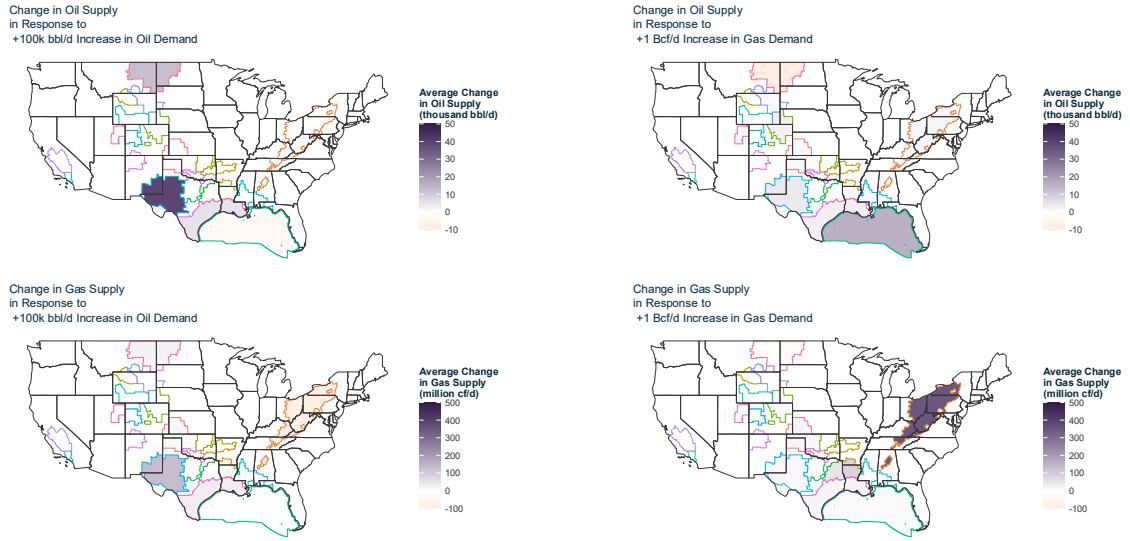
Figure 6. Marginal Supply Responses to WTI and Henry Hub Prices, by Basin



Note: Values are average basin-level supply responses in 2023–50. Basins with no positive marginal supply are shown in gray.

[28] Specifically, I use as weights well-level gas production during the baseline years of 2022-2023 and take weighted averages separately for each basin.

Figure 7. Marginal Supply Responses to Oil and Gas Demand Shocks, by Basin



Note: Values are average basin-level supply responses in 2023–50.

Figure 6 shows maps of the marginal supply responses of oil (top row) and gas (bottom row) in response to exogenous +1% increases in WTI prices (left column) and Henry Hub prices (right column). Figure 7 shows the analogous maps for the shocks to oil demand (left column) and gas demand (right column). Setting aside the relative magnitudes, the major difference between these maps is that the supply responses in Figure 6 are (almost) universally positive, whereas those in Figure 7 are positive or negative depending on the relative importance of oil versus gas prices in driving production outcomes across basins. County-level analogues of these maps can be seen in Appendix Figures A10 and A11.

5.7 Additional Sensitivity Analyses

Various sensitivity analyses confirm the robustness of the results. Figure 8 shows Monte Carlo distributions—reflecting uncertainty in the drilling elasticity parameters $\eta_{b,\ell}^{k}$ and the high-grading coefficients β^{k}—on the key outcomes of interest: the effective leak rate of marginal supply and the oil and gas price impacts from the two export demand shock scenarios. All outcomes of interest are statistically different from zero and from each other, with reasonably narrow uncertainty ranges.

Figure 8. Distribution of Effective Methane Leak Rates and Price Impacts from Export Demand Scenarios

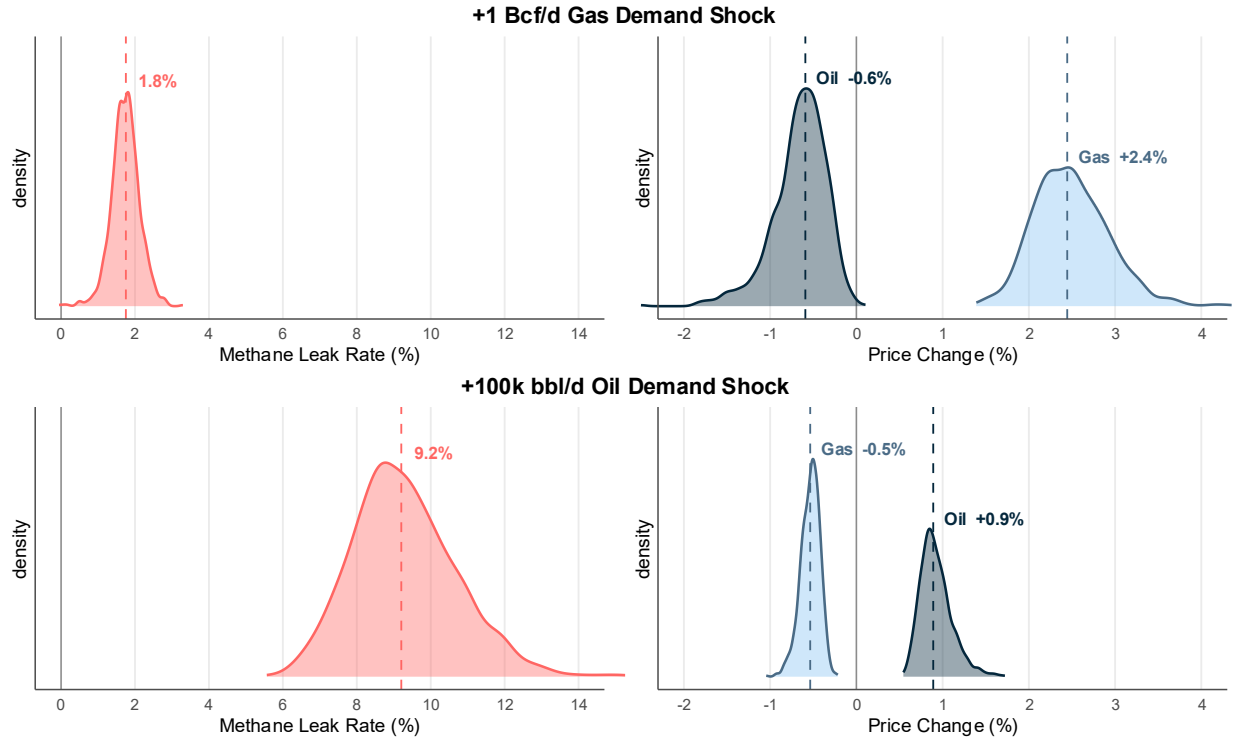
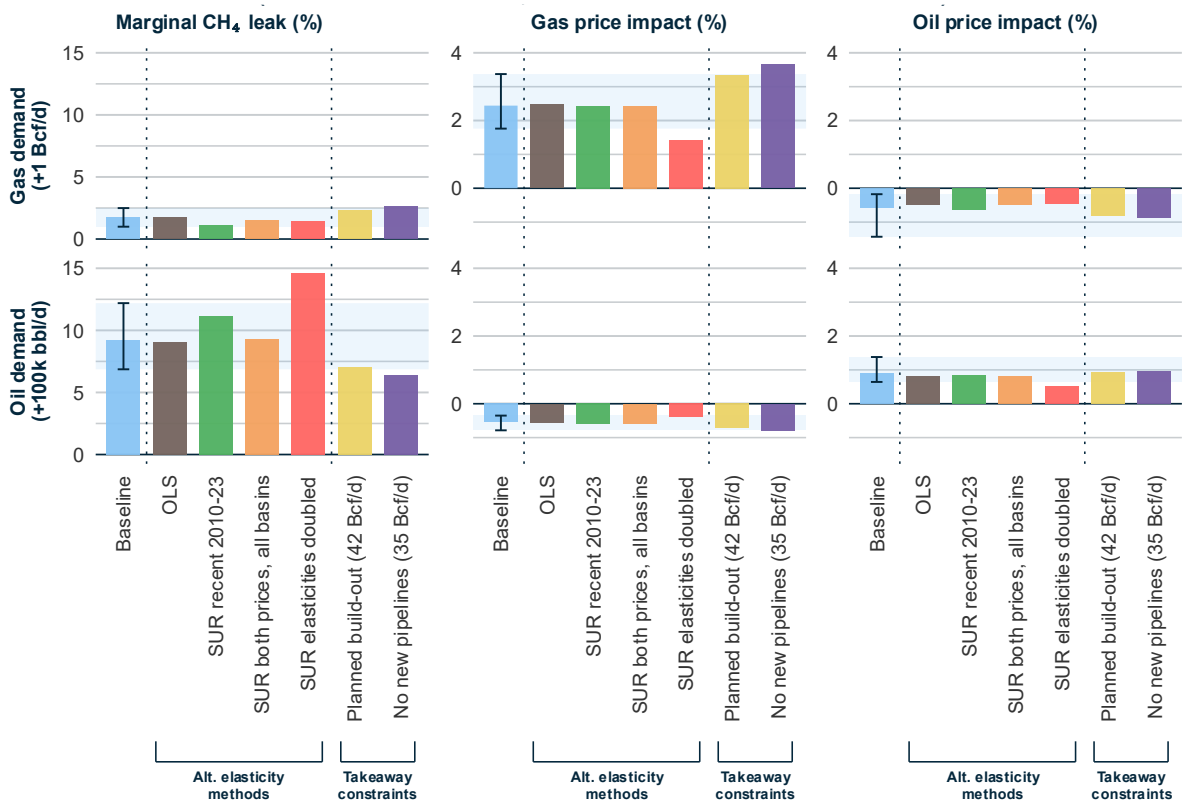


Figure 9 shows a series of sensitivities regarding 1) the estimated drilling elasticities and 2) the Appalachian pipeline takeaway capacity constraints that limit total basin-wide production. The whiskers and blue shaded area represent 95% confidence intervals on the base case estimated via Monte Carlo as shown in Figure 8.[29] All alternative elasticity estimation approaches produce effective methane leak rates and price impacts that are quantitatively similar and within the 95% confidence interval of the base case. The point estimates are very similar when using OLS (brown bar) instead of SUR and when including oil prices in gas plays and vice versa (orange bar). The estimation of the drilling elasticities over the more recent era of 2010-2023 (green bar)—a point at which the shale boom's impacts are largely baked in—can be interpreted in part as a sensitivity case that omits the 2006-2009 period when shale-era cost shocks most clearly pushed down gas prices, which arguably injects some downward bias in the estimated drilling elasticities with respect to gas prices. This scenario yields slightly larger drilling elasticities, although their confidence intervals overlap those of the base case (see Figure A6). Nonetheless, the larger point estimates amplify the directional finding of the base case: gas demand spurs disproportionately low-leak gas, while oil demand does the reverse. Finally, an assumed doubling the baseline elasticity estimates (red bar) produces results outside the 95% interval in certain cases, but these results again reinforce the directionality of the main findings regarding relative leak rates.

[29] Running Monte Carlos for all of the sensitivity cases would be computationally burdensome but would only reinforce the degree to estimated probability distributions overlap under the alternative approaches.

Capping Appalachian supply at 35 Bcf/d (consistent with no new pipelines, purple bar) or 42 Bcf/d (consistent with only currently planned pipelines being built, yellow bar) to reflect potential future binding takeaway constraints only modestly increases the low effective leak rates from gas export demand. This result owes in part to the relatively elastic and low-leak rate Arkla basin (including the Haynesville shale) filling about one third of the gas supply gap introduced by the cap on Appalachian output. However, meaningfully higher gas prices are needed to encourage that production growth. In the oil export demand scenario, the cap reduces the effective leak rate because it attenuates the margin by which Appalachian gas is crowded out by coproduced associated gas from the Permian basin.

Figure 9. Sensitivity Analyses: Effective Methane Leak Rate and Price Impacts under Alternative Approaches



Notes: Whiskers and blue shaded area represent 95% confidence intervals on the baseline scenario (SUR-based elasticities estimated on the full sample period, full pipeline Appalachia buildout to meet supply growth). Bcf/d values shown in takeaway constraints represent the cap imposed on total Appalachian gas production implied by the pipeline scenario.

Finally, Table A4 and Figure A12 show additional sensitivity analyses on methane leak rate inputs. Table A4 considers the sensitivity analysis in which I haircut basin-level leak rates by assumed factors of 0.75x, 0.50x, and 0.25x, for Appalachia, Permian, or both. Unsurprisingly, the resulting lower leak rates reinforce the main finding of low-leak gas supply in the gas demand case. In the oil demand case, the results are more nuanced: while haircutting the Permian leak

rate on its own naturally reduces the overall effective leak rate, even at 0.25x haircut the leak rate remains meaningfully above the 3.1% national average; on the other hand, haircutting Appalachian leak rates amplifies the crowding out effect, driving even higher effective leak rates than in the main case.[30] Figure A12 uses another source of methane leak rate estimates based on an inversion of satellite observations of atmospheric column methane concentrations from eight US regions (Estrada et al. 2026).[31] This data source estimates lower methane leak rates in most US basins including Appalachia and Permian, substantially reducing both the overall effective leak rates from both oil and gas demand scenarios. However, the relative magnitudes remain similar: in both the base case and the alternative, gas exports yield effective leak rates about 40% below the national average, while oil exports yield effective leak rates between 2.6 to 3 times the national average.

6. Comparison of Results with Those of Other LNG Studies

My results have two key takeaways for the likely impacts of increased LNG exports. First, each +1 Bcf/d of increased demand pull is estimated to increase gas prices by about 2.4%. Second, the incremental gas supply is estimated to come disproportionately (57%) from Appalachia, with very little (2%) coming from the Permian Basin, implying a lower-than-average marginal methane intensity (1.8% versus 3.1%). How do these results compare with the findings of other recent analyses of LNG exports?

First, my estimated gas price impact of about +2.4% per Bcf/d of gas exports is substantially larger than those found in three recent studies. For context, approximately 11 Bcf/d of new US LNG export capacity was under construction as of 2024Q4.[32] EIA (2023), DOE (2024), and Yergin et al. (2024; based on S&P Global's analysis) estimate price impacts of about +1.4%, +1.0%, and +0.75% per Bcf/d of exports, respectively. While the methods of Yergin et al. are somewhat of a black box, I can use the results of the EIA and DOE studies to compute the implied elasticities of US gas supply and demand. In both cases, the demand elasticities are close to zero (less than –0.1 in magnitude), while the supply elasticities are approximately 0.7 and 1 respectively, both of which appear to be based on the EIA's National Energy Modeling System (NEMS). These elasticities are substantially larger than the gas supply elasticity of less than 0.3 that I estimate, which explains why my estimated price impacts are larger.

[30] Shrinking Appalachian supply contributes negative terms (i.e., emissions reductions) to the weighted average leak rate. When those leak rates are adjusted downward, those negative terms are smaller, increasing the total.
[31] In this scenario, base-case leak rates based on Sherwin et al. (2024) are replaced with the values for the basins covered by Estrada et al. (2026). This includes Appalachia, Permian, Arkla, Texas and Louisiana Gulf Coast, Anadarko, East Texas, Fort Worth, San Juan, Piceance, and Uinta.
[32] If I model an exogenous 11 Bcf/d increase in gas export demand, I find a 30% increase in gas prices, confirming the roughly linear nature of the price effect.

Second, the 1.8% weighted average methane leak rate from marginal supply is about halfway between the value of 0.56% used by DOE (2024) and the 2.8% value used in Howarth (2024). While Howarth's value is meant to represent methane leak rates in the Permian Basin, my results suggest very little (2%) of marginal gas supply in response to LNG export demand is likely to come from the Permian. The DOE's value, by contrast, is likely too low because it is based on US Environmental Protection Agency inventories that are well known to undercount methane emissions (see, e.g., Alvarez et al. (2018)). However, an important caveat is that substantial uncertainty remains about whether observed methane leak rates will improve or persist into the future.

Finally, the very high effective methane intensity of marginal gas supply in response to an increase in oil demand suggests that the 2015 repeal of the crude oil export ban may have had larger, but less appreciated, consequences for driving US methane emissions than those from the arguably higher-profile LNG export pause. Specifically, model results suggest that historical growth in crude oil exports during 2015–25 may have caused about twice as much methane emissions as US LNG exports over that period, with the former's methane impacts equivalent to those expected to be caused by 20-31 Bcf/d of gas export demand, which is approximately the amount of future export capacity under consideration.

7. Conclusion

This paper expands the Dynamic Oil and Gas Market Analysis (DOGMA) model to estimate the impacts of increased US oil and gas export demand on domestic oil and gas prices, marginal oil and gas supply by US basin, and the implied weighted-average methane intensity of marginal gas supply. Each exogenous 1 Bcf/d increase in gas export demand is estimated to increase domestic natural gas prices by approximately 2.4%, while reducing crude oil prices by 0.6% as a result of the induced supply of coproduced oil. The US supply response comes disproportionately from basins with low estimated leak rates, led by Appalachia, yielding a weighted-average methane intensity of the gas supply expected to meet export demand (1.8%) that is lower than average gas supply (3.1%). The supply response to an exogenous oil demand increase shows the reverse pattern, with high-leak Permian supply crowding out low-leak basins like Appalachia, yielding a very high weighted-average methane leak rate (9.2%). While the recent expansion of US LNG exports has attracted considerable attention for its methane intensity, these results suggest that the 2015 repeal of the crude oil export ban may have driven twice as much methane emissions as have been caused by US LNG exports during the 2015 to 2025 period, with the former equivalent to the methane emissions expected to be caused by 20-31 Bcf/d of gas exports.

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Supplemental Appendix for "Where Does the Marginal Methane Molecule Come From? Implications of LNG Exports for US Natural Gas Supply and Methane Emissions"

Brian C. Prest

November 11, 2026

Figure A1. Well Map

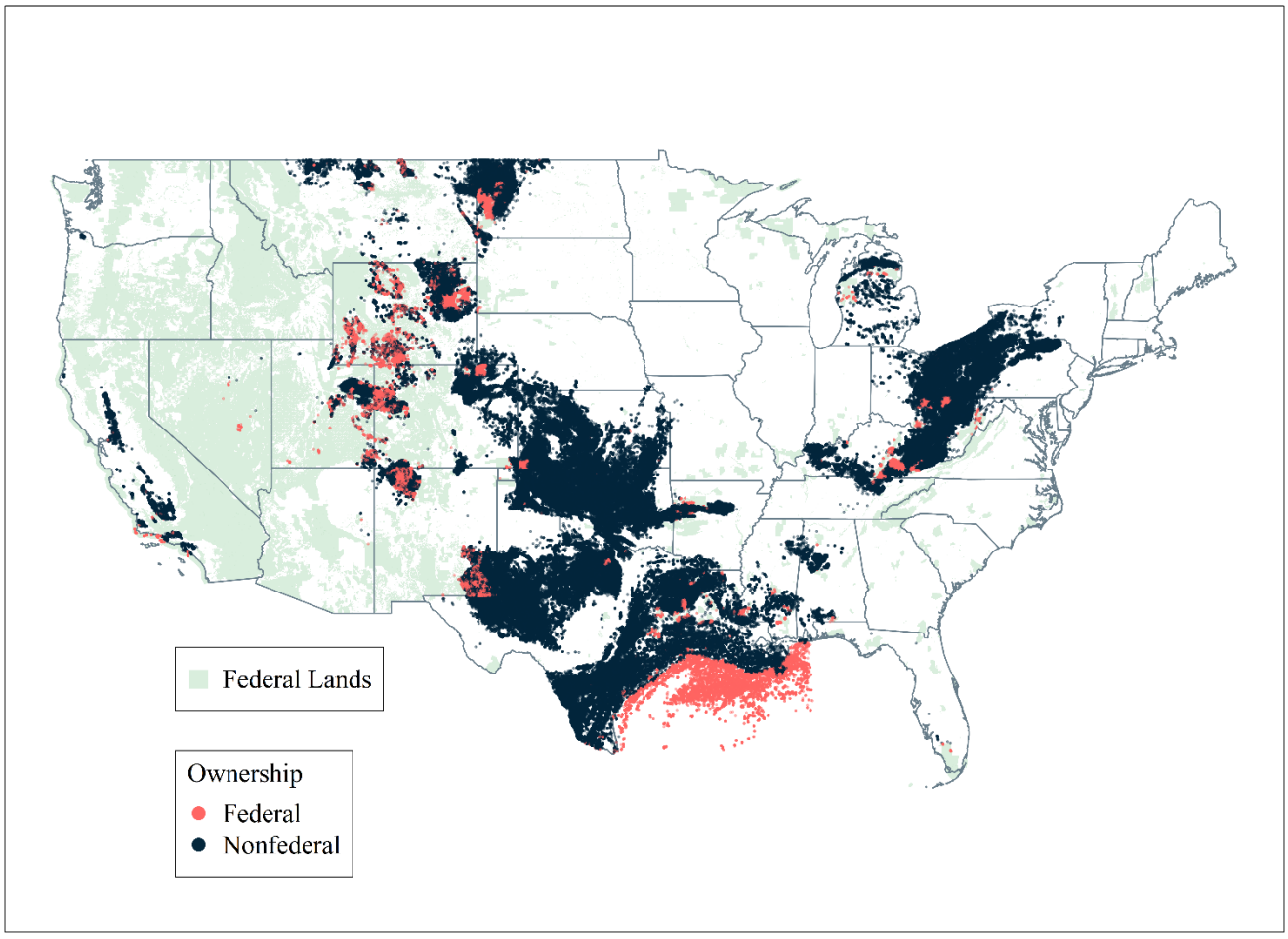
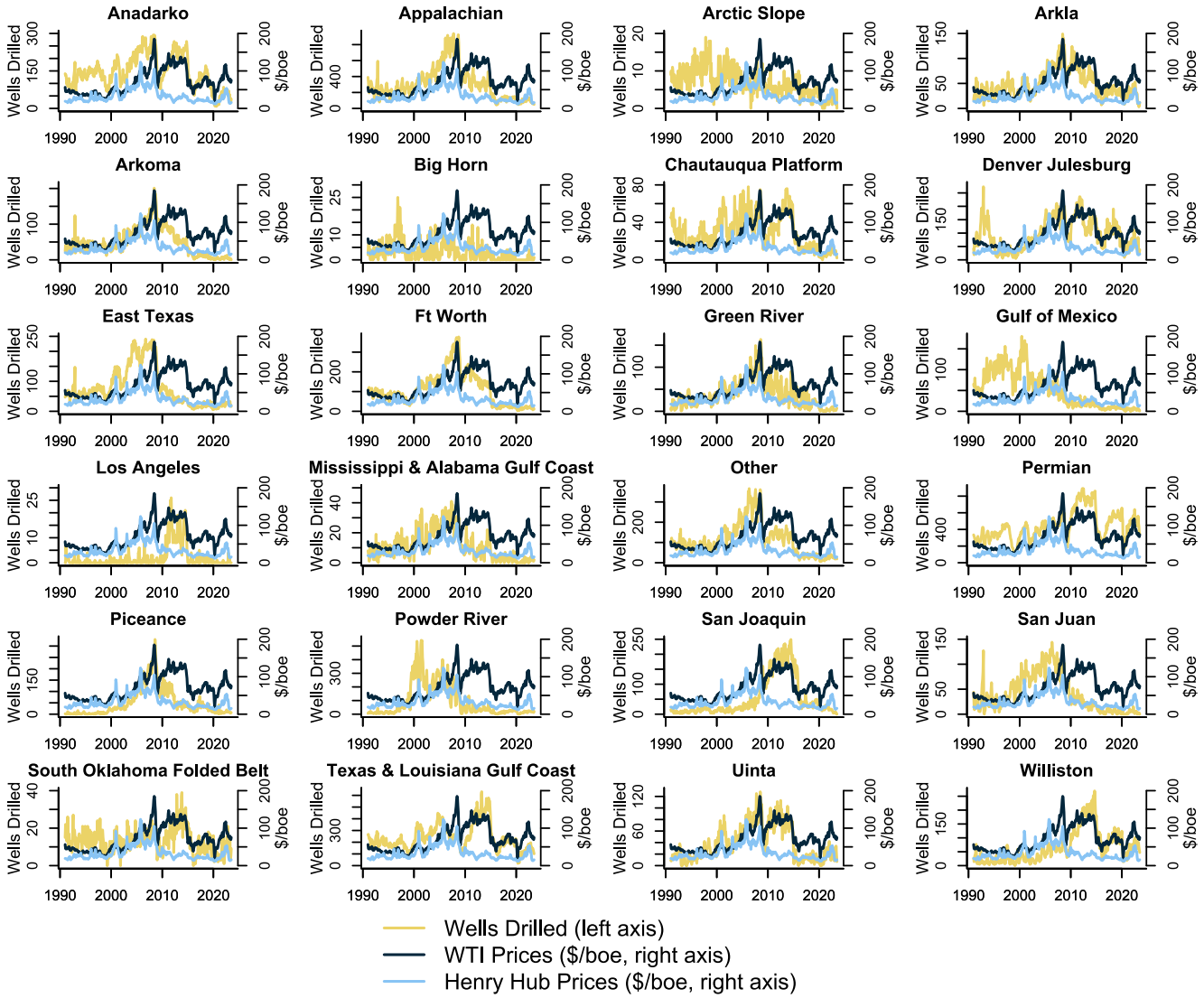
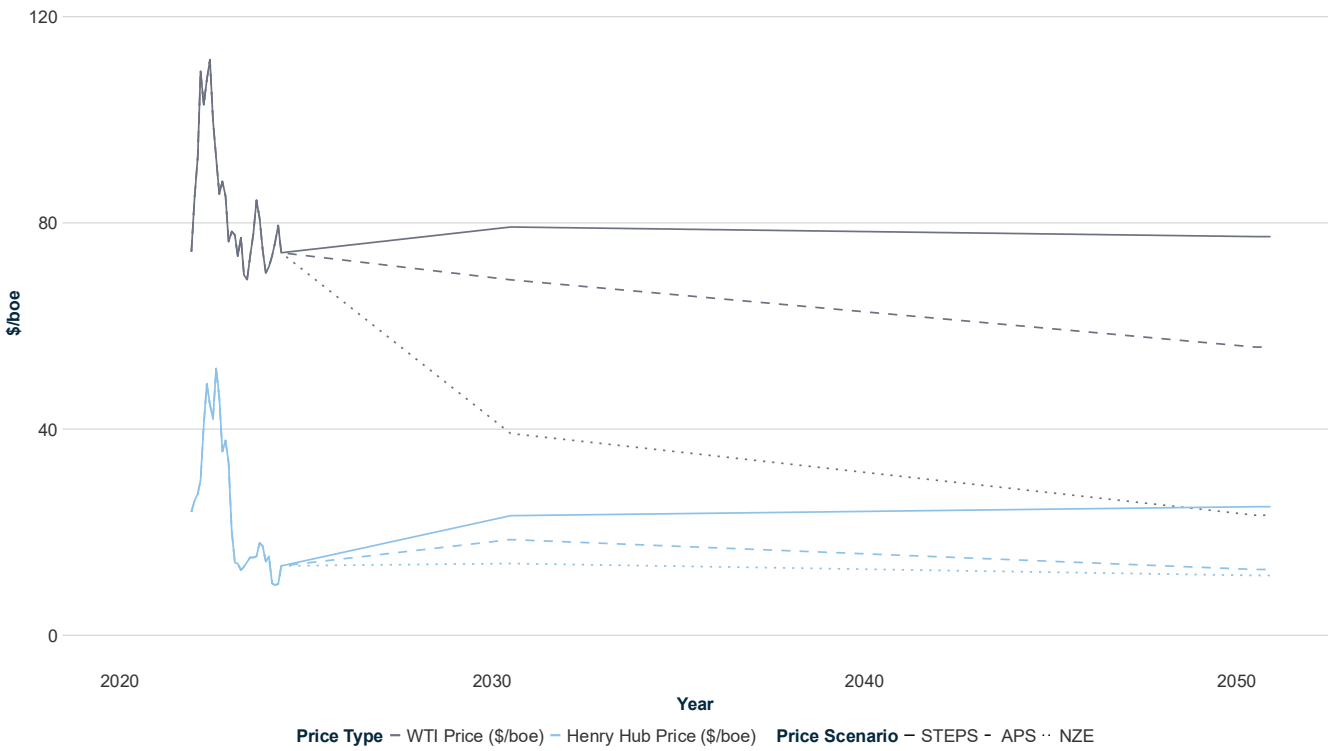


Figure A2. Drilling Activity, by Basin, Versus WTI Crude and Henry Hub Gas Prices



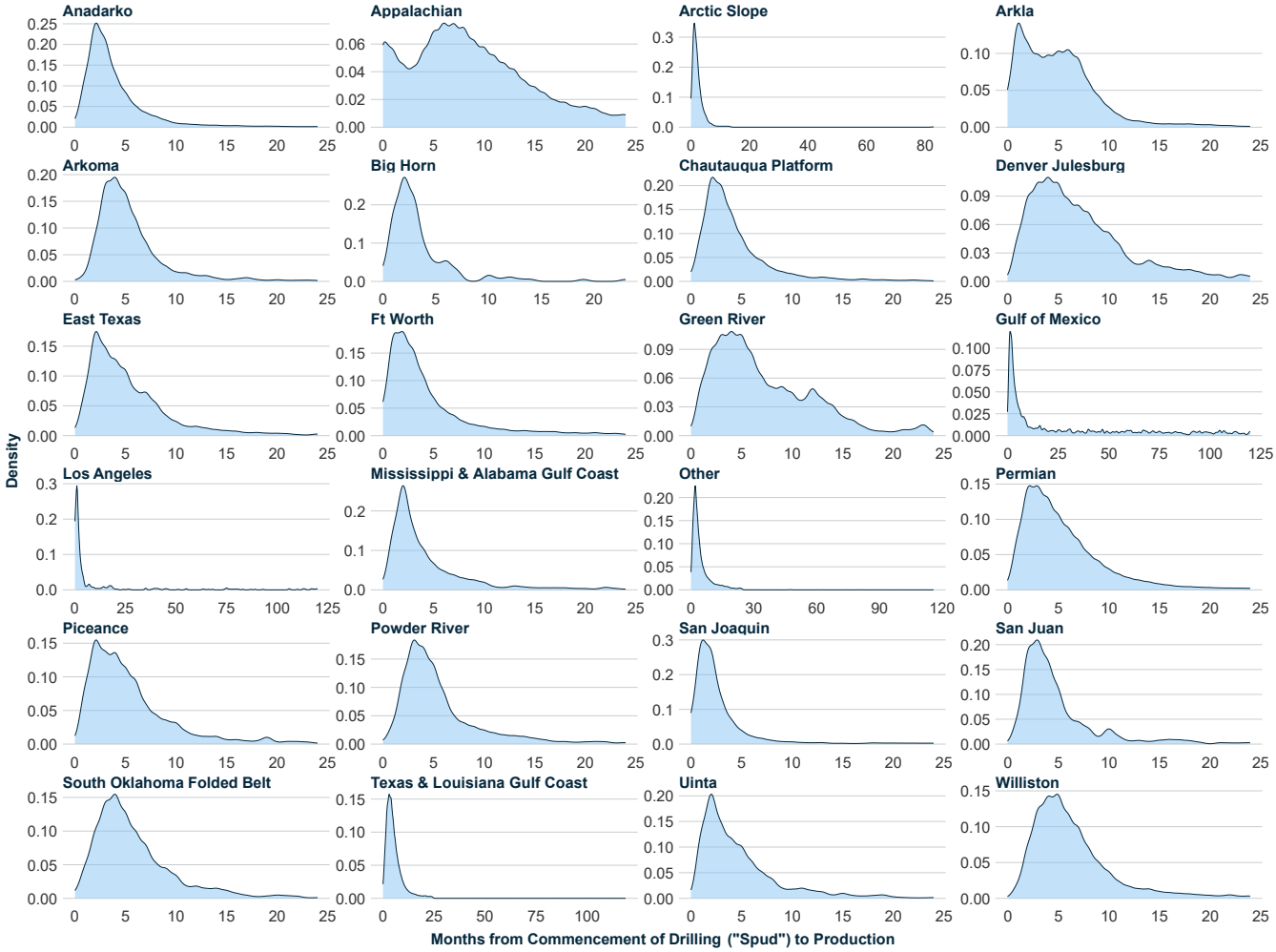
Note: WTI and Henry Hub prices are the same in each panel. Henry Hub prices are converted into barrels of oil equivalent (boe) by multiplying by 5.8 MMBtu/boe.

Figure A3. Future Price Paths



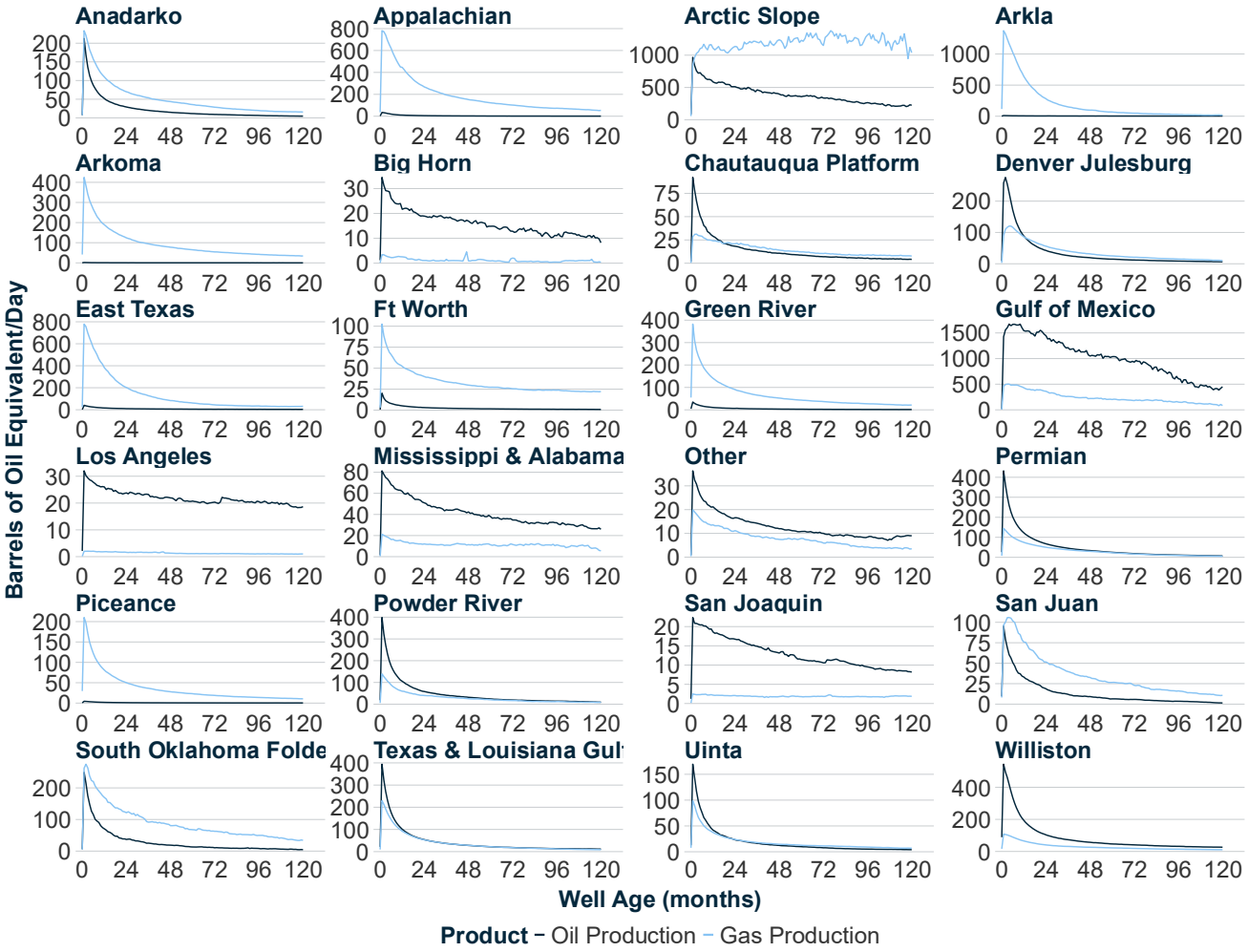
Note: Henry Hub prices are converted into barrels of oil equivalent (boe) by multiplying by 5.8 MMBtu/boe. STEPS = Stated Policies Scenario; APS = Announced Pledges Scenario; NZE = Net Zero Emissions by 2050.

Figure A4. Densities of Time from Spud to Production, by Basin



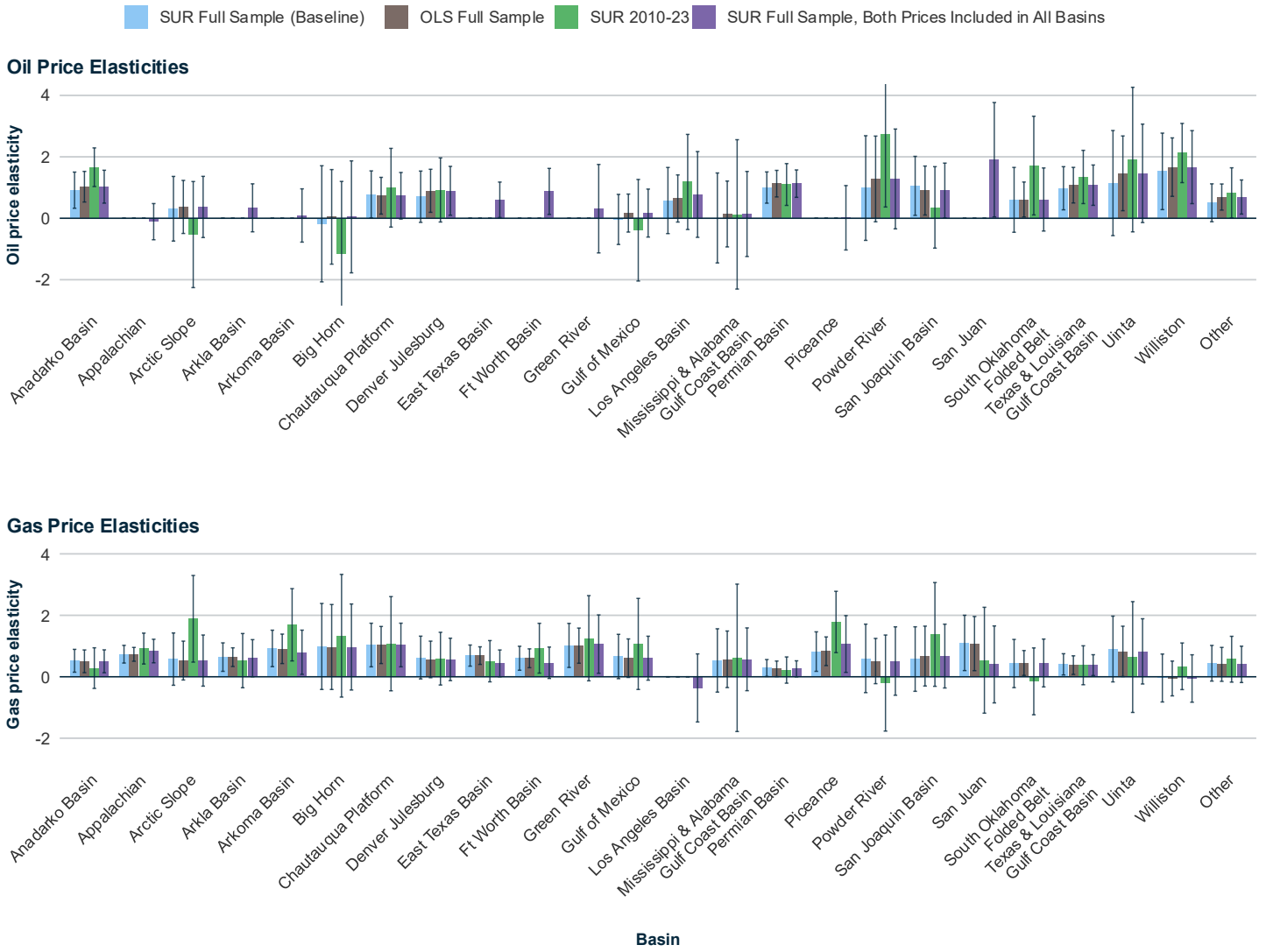
Note: Density bandwidth used is 0.5 months. The *x*-axis extends to 2 years for onshore-only basins but 10 years for basins with offshore drilling activity (e.g., the Gulf of Mexico, Los Angeles, and Texas & Louisiana Gulf Coast basins). Dataset includes wells entering production since 2012 with spud-to-production times not deemed data errors (≤24 months onshore and ≤120 months offshore).

Figure A5. Production Profiles, by Basin



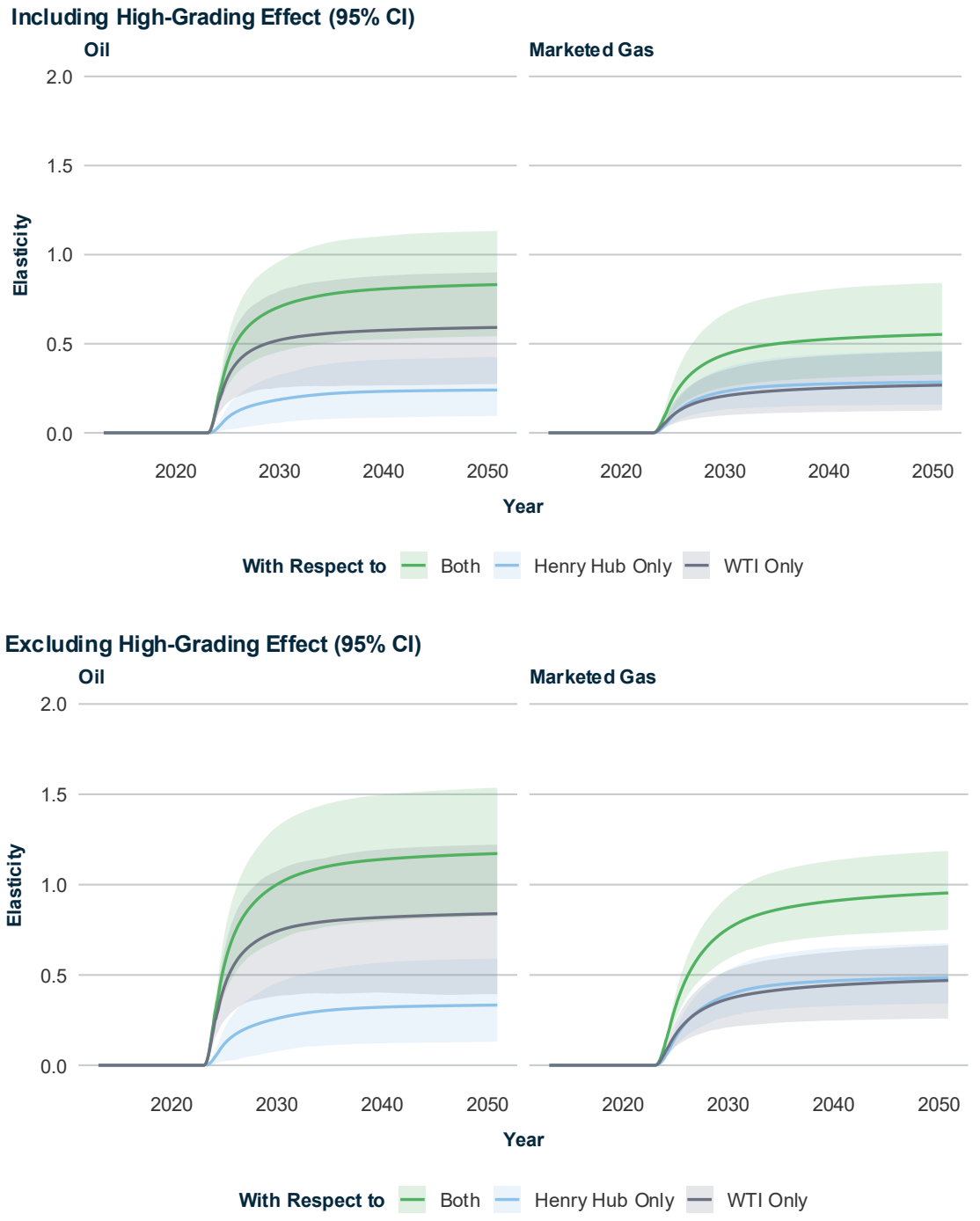
Note: Figures represent within-basin average production rates by month among wells beginning production in 2012–24. Profiles represent gross withdrawals, not marketed production; the distinction between the two is most important in Alaska (Arctic Slope), where only about 10% of gross gas withdrawals are sent to market, as much is reinjected. Gas production is converted to barrels of oil equivalent (boe) by dividing production in thousand cubic feet (mcf) by 6 mcf/boe.

Figure A6. Long-run Drilling Elasticities Under Alternative Estimation Methods



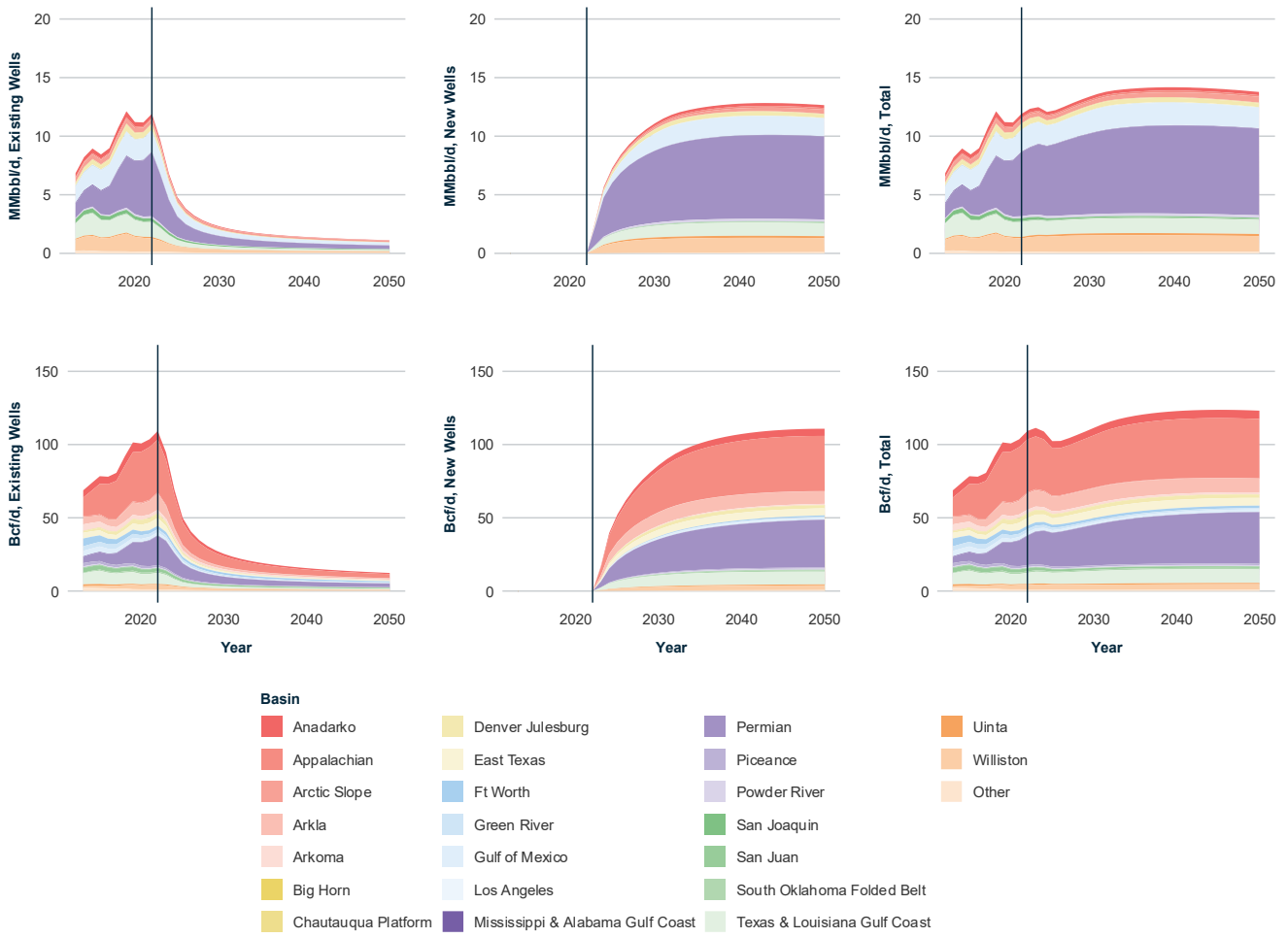
Note: Figure compares oil- and gas-price elasticities of drilling from the baseline method (SUR on the full Feb-1992 to July-2023 sample) to three alternative approaches: i) OLS on the full sample, ii) SUR on the restricted sample of 2010-2023, and iii) SUR on the full sample without excluding oil prices from pure gas basins or gas prices from pure oil basins. See Figure A1 for basin-specific drilling activity over time.

Figure A7. Time-Varying Response of US Oil and Gas Production to an Exogenous, Permanent 1% Increase in Oil or Gas Prices in 2023, Expressed in Elasticity Terms



Note: The top panel includes response of initial production to increased drilling ("high-grading"); the bottom panel excludes that effect. An excel file containing these time series of elasticities can be downloaded at https://www.dropbox.com/scl/fi/biipiy37r4jpy2fp9ghq1/Prest-2026-Elasticities.xlsx?rlkey=rhfbiskyohrfsqdna6wof9y5f&dl=1

Figure A8. Projected US Oil and Marketed Gas Production from Existing Wells, New Wells, and Combined, Under the APS Price Scenario



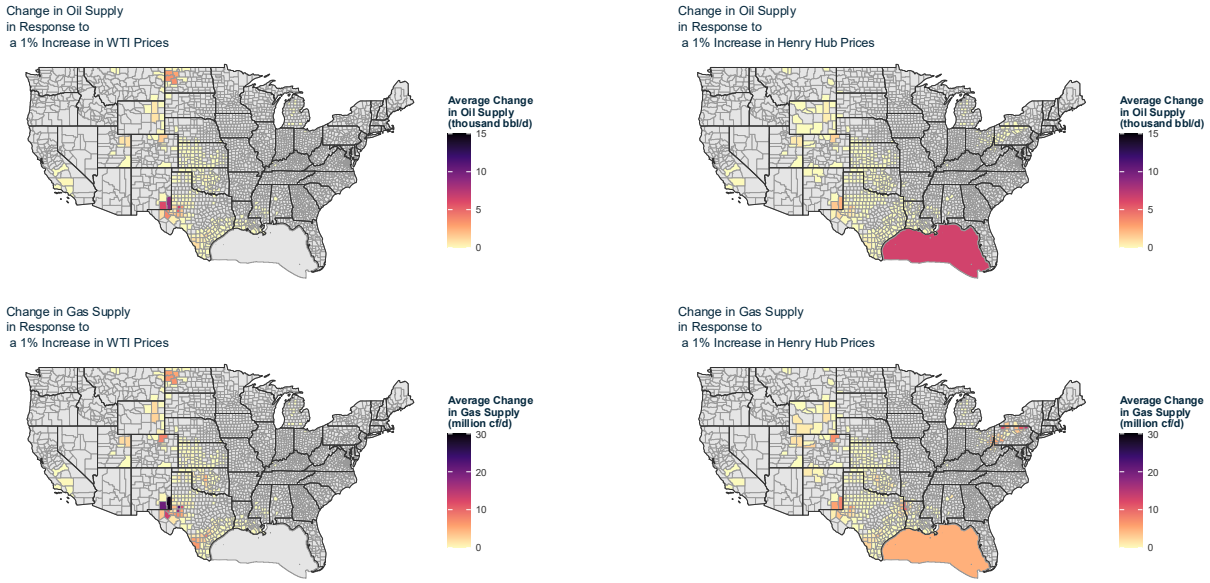
Note: The five basins contributing the most to oil supply in 2050 are, in order, the Permian (purple), Gulf of Mexico (light blue), Williston (light orange at bottom), Texas & Louisiana Gulf Coast (light green), and Arctic Slope (light coral), which collectively account for 88% of oil production that year. The five basins contributing the most to gas supply in 2050 are Appalachia (coral), Permian (purple), Texas & Louisiana Gulf Coast (light green), Arkla (light coral), and Anadarko (dark coral), which collectively account for 79% of gas production that year.

Figure A9. Projected US Oil and Marketed Gas Production from Existing Wells, New Wells, and Combined, Under the NZE Price Scenario



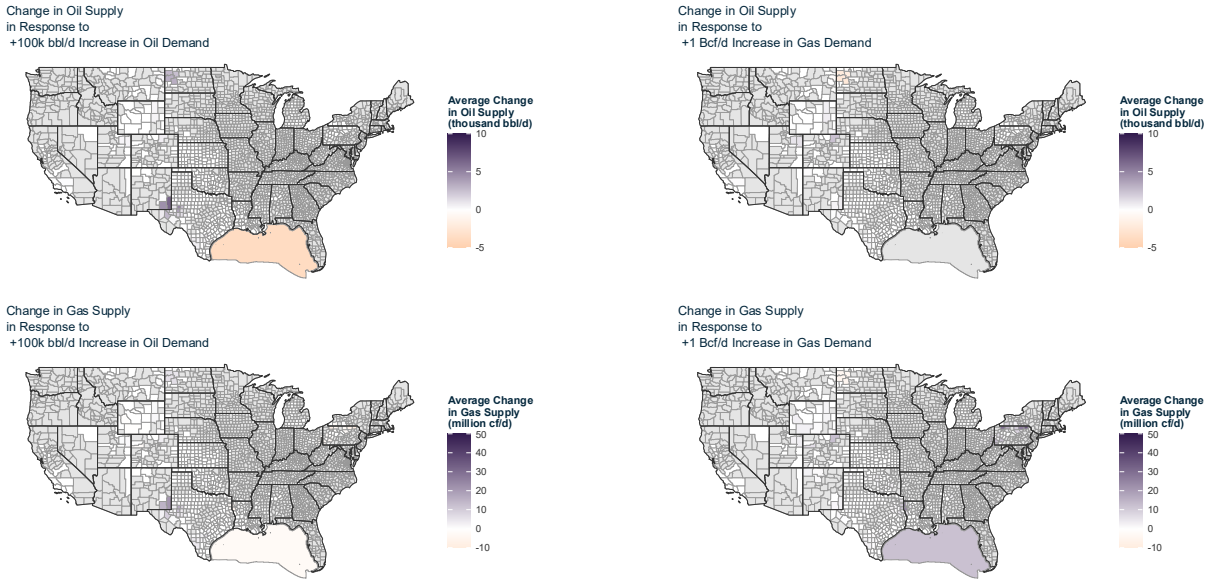
Note: The five basins contributing the most to oil supply in 2050 are, in order, the Permian (purple), Gulf of Mexico (light blue), Williston (light orange at bottom), Texas & Louisiana Gulf Coast (light green), and Arctic Slope (light coral), which collectively account for 87% of oil production that year. The five basins contributing the most to gas supply in 2050 are Appalachia (coral), Permian (purple), Arkla (light green), Texas & Louisiana Gulf Coast (light green), and East Texas Basin (light yellow), which collectively account for 79% of gas production that year.

Figure A10. Marginal Supply Responses to WTI and Henry Hub Prices, by County



Note: Values are average supply responses in 2023–50. Counties with no positive marginal supply are shown in gray.

Figure A11. Supply Responses to Oil and Gas Demand Shocks, by County



Note: Values are average supply responses in 2023–50. Counties with zero marginal supply are shown in gray.

Table A1. Basin-Level Elasticities, Methane Leak Rates, and Gas Supply Shares

				Gross gas supply share (%)					
	Drilling elasticity with respect to…			Average		Marginal in response to …			
Basin	Henry Hub prices	WTI prices	Methane leak rate (%)	Historical (2022)	Projected (2023–50)	+1% Henry Hub price	+1 Bcf/d gas demand	+1% WTI price	+100k bbl/d oil demand
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Appalachian	0.73	—	1.0%	30%	31%	44%	57%	0%	-79%
Permian	0.29	1.00	5.3%	18%	26%	15%	2%	57%	133%
Arkla	0.64	—	1.0%	9%	8%	11%	14%	0%	-19%
Texas & Louisiana Gulf Coast Basin	0.40	0.98	4.6%	7%	8%	7%	3%	17%	36%
Arctic Slope	0.57	0.31	2.7%	7%	3%	1%	2%	1%	-0%
Anadarko	0.52	0.91	4.6%	5%	4%	4%	3%	8%	15%
East Texas	0.69	—	4.6%	5%	5%	7%	9%	0%	-12%
Williston	-0.04	1.53	4.6%	3%	3%	-0%	-3%	9%	25%
Denver Julesburg	0.63	0.70	1.1%	3%	2%	3%	3%	3%	4%
Green River	1.02	—	4.6%	2%	1%	1%	1%	0%	-1%
Ft Worth	0.60	—	3.1%	2%	1%	1%	1%	0%	-1%
Arkoma	0.92	—	1.0%	2%	1%	1%	1%	0%	-2%
Gulf of Mexico	0.66	-0.04	2.7%	2%	1%	1%	2%	-0%	-3%
San Juan	1.10	—	1.0%	2%	1%	1%	1%	0%	-1%
Other	0.44	0.50	2.7%	1%	1%	0%	0%	0%	1%
Piceance	0.82	—	1.0%	1%	1%	1%	1%	0%	-2%
South Oklahoma Folded Belt	0.43	0.60	4.6%	1%	1%	1%	0%	1%	1%
Uinta	0.90	1.15	5.7%	1%	1%	1%	1%	1%	2%
Powder River	0.60	0.98	4.6%	1%	1%	1%	1%	2%	3%
San Joaquin	0.58	1.05	2.5%	0%	0%	0%	0%	0%	0%
Chautauqua Platform	1.03	0.78	4.6%	0%	0%	0%	0%	0%	0%
Mississippi & Alabama	0.53	0.01	4.6%	0%	0%	0%	0%	0%	-0%
Big Horn	0.99	-0.18	2.7%	0%	0%	0%	0%	-0%	-0%
Los Angeles	—	0.58	2.7%	0%	0%	0%	-0%	0%	0%
Weighted-average methane leak rate in column 3, using columns 4–9 as weights				**2.8%**	**3.1%**	**2.5%**	**1.8%**	**4.9%**	**9.2%**

Note: Basins are sorted in order of column 4, the 2022 gas supply share. Supply share columns 4–9 sum to 100%. Shares represent shares of gross withdrawals, not marketed gas. This distinction is important primarily for the Arctic Slope, where only 10% of gross withdrawals make it to market, with most being reinjected.

Table A2. Basin-Level Elasticities, Methane Leak Rates, and Oil Supply Shares

				Oil supply share (%)					
	Drilling elasticity with respect to...			Average		Marginal in response to ...			
Basin	Henry Hub prices	WTI prices	Methane leak rate (%)	Historical (2022)	Projected (2023–50)	+1% Henry Hub price	+1 Bcf/d gas demand	+1% WTI price	+100k bbl/d oil demand
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Permian	0.29	1.00	5.3%	46%	53%	46%	15%	63%	69%
Gulf of Mexico	0.66	-0.04	2.7%	15%	13%	20%	55%	0%	-7%
Texas & Louisiana Gulf Coast Basin	0.40	0.98	4.6%	11%	9%	11%	11%	10%	10%
Williston	-0.04	1.53	4.6%	10%	10%	-1%	-32%	17%	23%
Denver Julesburg	0.63	0.70	1.1%	4%	3%	5%	10%	2%	1%
Arctic Slope	0.57	0.31	2.7%	3%	3%	3%	7%	1%	-0%
Anadarko	0.52	0.91	4.6%	3%	2%	3%	5%	2%	2%
San Joaquin	0.58	1.05	2.5%	2%	1%	0%	0%	0%	0%
Powder River	0.60	0.98	4.6%	1%	2%	3%	5%	2%	2%
Other	0.44	0.50	2.7%	1%	1%	1%	1%	0%	0%
Appalachian	0.73	—	1.0%	1%	1%	2%	7%	0%	-1%
Uinta	0.90	1.15	5.7%	1%	1%	4%	8%	2%	1%
South Oklahoma Folded Belt	0.43	0.60	4.6%	1%	1%	1%	1%	0%	0%
Mississippi & Alabama Gulf Coast Basin	0.53	0.01	4.6%	0%	0%	0%	0%	0%	-0%
Chautauqua Platform	1.03	0.78	4.6%	0%	0%	1%	2%	0%	0%
East Texas	0.69	—	4.6%	0%	0%	0%	1%	0%	-0%
Los Angeles	—	0.58	2.7%	0%	0%	0%	-0%	0%	0%
San Juan	1.10	—	1.0%	0%	0%	0%	1%	0%	-0%
Big Horn	0.99	-0.18	2.7%	0%	0%	0%	0%	-0%	-0%
Green River	1.02	—	4.6%	0%	0%	0%	1%	0%	-0%
Arkla	0.64	—	1.0%	0%	0%	0%	0%	0%	-0%
Ft Worth	0.60	—	3.1%	0%	0%	0%	0%	0%	-0%
Piceance	0.82	—	1.0%	0%	0%	0%	0%	0%	-0%
Arkoma	0.92	—	1.0%	0%	0%	0%	0%	0%	-0%

Note: Basins are sorted in order of column 4, the 2022 oil supply share. Supply share columns sum to 100%. Columns are in the same order as in Table 3 in the main text and Appendix Table A1 for comparison.

Table A4. Marginal methane leak rate (%) under basin-level haircuts to leak-rate

	+1 Bcf/d Gas Demand			+100k bbl/d Oil Demand		
	Which Basin is Haircut					
Haircut Factor	Appalachia	Permian	Both	Appalachia	Permian	Both
None (100%)	1.75%	1.75%	1.75%	9.20%	9.20%	9.20%
75%	1.61%	1.72%	1.58%	9.40%	7.45%	7.64%
50%	1.47%	1.69%	1.41%	9.59%	5.69%	6.08%
25%	1.33%	1.66%	1.24%	9.79%	3.93%	4.51%

Figure A12. Effective leak rates (%) under alternative methane leak data

