Electric Sector Capacity Planning under Uncertainty: Shale Gas and Climate Policy in the US*

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Abstract

This research investigates how uncertainties related to shale gas production will influence the long-term deployment of supply-side technologies in US electricity markets, particularly under uncertain climate policy constraints. Using a two-stage stochastic programming approach, model results suggest that there is considerable value to limiting fugitive methane emissions from shale gas. This strategy would give the electric sector the flexibility of waiting to observe the resolution of uncertainties before building new capacity. Information about the stringency of greenhouse gas abatement is most valuable to utilities and generators when tight emissions caps are realized. The stochastic solution is especially valuable if no pre-2030 mitigation is assumed, if the uncertainty resolution date is delayed, or if the social cost of carbon is incorporated into the calculations.

Keywords: Electricity, uncertainty, stochastic programming, shale gas

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1 Introduction

Recent advances in technologies like horizontal drilling and hydraulic fracturing have caused rapid increases in production from unconventional natural gas resources like shale formations. However, the same technologies that have facilitated this growth have also raised important questions about their environmental impacts. Natural gas is broadly considered to be a more environmentally benign alternative to coal due to its lower CO_2 emissions from combustion and its avoidance of pollutants like sulfur, particulate matter, and mercury. These environmental benefits, combined with abundant reserves, suggest that unconventional gas can play an important role in national and international energy policy: bridging a transition to a lower-carbon economy, reshaping energy security, and altering investment decisions in the electric power sector [1, 2].

Despite these attractive features, the environmental impacts of shale gas production on air quality, water quality, geology, and greenhouse gas emissions are currently being questioned. One of the most contentious and uncertain issues centers on the greenhouse gas impacts of unconventional natural gas development. Research on lifecycle emissions from shale gas production has only been undertaken in the past year. These existing studies exhibit a high degree of variation due to divergent assumptions and considerable uncertainty in the underlying data [3, 4, 5, 6, 7, 8, 9, 10]. These problems are compounded by empirical data scarcities and the heterogeneity of sites and drilling practices.

The objective of this research is to investigate how the uncertainties related to unconventional natural gas will impact the deployment of supply-side technologies in US electricity markets through 2050. In particular, this paper looks at how uncertainties in future natural gas prices, upstream methane emissions, the global-warming potential of methane, and the stringency of federal climate policy will influence optimal abatement efforts. The model is the first to incorporate upstream emissions from shale gas production into an energy-economic model that can examine tradeoffs between lifecycle costs and environmental impacts of different technologies, particularly in a stochastic programming setting.

2 Capacity Planning under Uncertainty

2.1 Overview

The problem of capacity planning in the electric power sector is well suited to the stochastic control paradigm where strategies adjust over time as new information becomes available about technologies, resources, and polices. Decisions about generating capacity expansion and operation take place against long and highly uncertain planning horizons. Uncertainties about developments in the system environment impact the cost-effectiveness of planning decisions, particularly for utilities whose long-lived and essentially irreversible capital investments are designed to last many decades. The long lead-times and lifetimes of capital in energy system projects mean that the environment in which power plants come online and operate may be very different from the one in which they are planned. Hence, suboptimal near-term decisions that fail to account for a range of potential natural gas price scenarios and lifecycle emissions, for instance, can cost ratepayers, investors, and taxpayers and have important long-term environmental implications.

Planning in the US electric power industry has been shrouded in substantial uncertainty in recent decades, and the simultaneous challenges with which the sector must grapple are only expected to increase in the future. Progressively stringent environmental policies, especially related to climate change, may require emission controls alongside early retirements and fuel switching. Complying with federal and state regulations must happen while utilities concurrently struggle with an aging fleet of generators and abrupt changes in the economics of fossil fuels due to the dramatic expansion in shale gas development. These factors make it even more important for power system planners to develop strategies that hedge against a variety of possible futures and that explicitly consider both the expected costs and robustness of proposed plans.

2.2 Uncertainties Considered in Analysis

Focusing on the role of shale gas in a carbon-constrained world, this analysis represents five uncertain model parameters as random variables, including the stringency of climate policy, natural gas price path, coal price path, global-warming potential of methane, and upstream emissions from shale gas. Although global climate change is an urgent and significant problem, there are many sources of uncertainty that will determine the stringency of policy measures used to curb greenhouse emissions in the US [11]. Utilities and generators consider the timing, form, and stringency of climate policies uncertain. This analysis assumes that the policy will take the form of cumulative emissions caps on equivalent greenhouse gas emissions, since climate outcomes depend on concentrations of greenhouse gases in the atmosphere. The support of this random variable contains five elements that correspond to cumulative caps with annual emissions equivalents of 3000, 2500, 2000, 1500, and 1000 million metric tons of carbon dioxide equivalent (Mt-CO_2e) per year. The most stringent case is comparable to the American Clean Energy and Security Act of 2009 (more commonly known as the Waxman-Markey bill). After an informal expert elicitation, the probabilities associated with these outcomes are assumed to be 0.1, 0.2, 0.4, 0.2, and 0.1, respectively.

Prices for energy resources are uncertain and fluctuate based on many complex factors. Uncertainty about the future of natural gas is also driven by recent discoveries and increased domestic production of shale gas [12]. Although abundant gas resources suggest expanded use in the electricity sector, uncertainty about the environmental impacts of production and long-run production costs make the extent of this growth unclear [2, 13]. Additionally, natural gas price uncertainty will be influenced by the unknown policy environment, public acceptance of hydraulic fracturing [14], and uncertainty surrounding life-cycle emissions for shale gas [7, 9]. The stochastic parameter in the model representing this uncertainty is the natural gas price annual growth rate. Based on the EIA's estimates of this value under baseline, low shale estimate ultimate recovery, and high ultimate recovery cases [2], this analysis uses growth rates of 0, 0.7, 1.4, 2.1, and 2.8 percent with probabilities of 0.1, 0.2, 0.4, 0.2, and 0.1, respectively.

Coal prices, though less uncertain than natural gas, are important to treat as random parameters, since even comparatively minor increases can change the economics of building and operating coal-fired power plants with and without carbon capture. Using EIA estimates [2], this uncertainty is incorporated as the annual growth rate for coal prices. The three possible realizations of the random parameter are 0, 0.5, and 1.0 percent and have corresponding probabilities of 0.25, 0.5, and 0.25, respectively.

Although methane leaks represent only a few percent of the lifetime production of a well, methane is the dominant portion of natural gas and a potent greenhouse gas, which means that even small leaks of this short-lived climate forcer are significant. Recent modeling efforts [15] have suggested that methane may have an even larger GWP than previous estimates suggested [11], particularly when indirect effects on atmospheric aerosols are taken into account. This analysis uses estimates of the GWP for methane from [15] and uses a 100-year timescale to analyze the impact of methane. This random variable has outcomes of 25, 33, and 42 with probabilities of 0.25, 0.5, and 0.25, respectively.

As described in Section 1, the upstream methane emissions associated with shale gas production are uncertain. Fig. 1 illustrates the disagreement and uncertainty in this value across existing studies. This work uses these values in a distribution with outcomes of 0.11, 0.6, and 1.18 grams of carbon per megajoule of fuel with probabilities of 0.25, 0.5, and 0.25, respectively.[1]

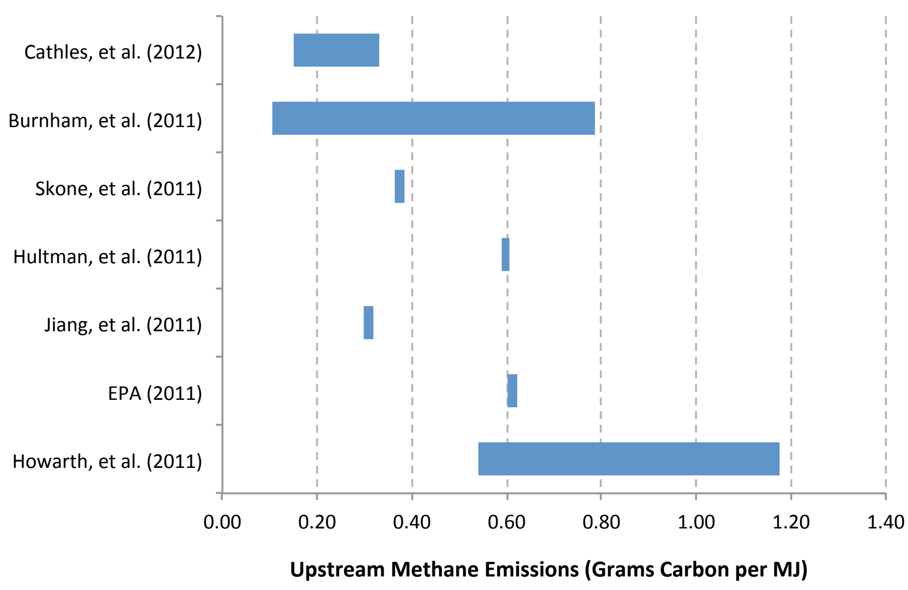

Figure 1: Estimates of fugitive methane emissions from shale gas production from existing literature.

[1]This distribution may err on the conservative side of leakage estimates. A recent study by Petron, et al. [16] is one of the first to use actual air samples to characterize emissions of methane. Using daily samples from the NOAA Boulder Atmospheric Observatory in Colorado, the multi-species analysis estimates that natural gas production in the Denver-Julesburg Basin leaks methane at a rate that is twice as high as the Howarth, et al. estimates for wellhead completion and production. The analysis does not quantify methane emissions from other stages of the natural gas lifecycle like leaks during distribution.

3 Modeling Approach

3.1 Deterministic Electricity Capacity Expansion Model

To answer these research questions, the author developed a capacity planning model of the US electric power sector. This GAMS model determines optimal capacity investment and production decisions for the US electric sector between 2007 and 2050 in ten-year increments with three load segments per year.[2] The model uses a partial equilibrium framework with exogenous fuel prices. Data for the model come from a variety of public sources, as shown in Table 1.

Table 1: Data sources for model inputs

Data	**Source**
Capital and O&M costs	EIA [17]
Existing capacity	Form EIA-860 [18]
Availability and capacity factors	EPA National MARKAL Database 2010
Fuel prices	EIA Annual Energy Outlook [2]
Load	Based on Form EIA-860 [18]

The model assumes that capacity installation and electricity production decisions are centrally coordinated among all utilities and generators. In the core deterministic model, utilities minimize the sum of discounted energy system costs for all capacity blocks during all periods. The decision variables and parameters in the objective function are:

Decision Variables

- x_i^t new capacity investment of generation technology i decided at time period t (GW)
- w_i^t installed capacity of type i available at time t (GW)
- y_{ij}^t generation of type i during load segment j at time t (GWh)
- u_s^t reduced demand from step s in the demand curve at time t (GW)
- v^t emissions offset purchases at time t (Mt-CO_2e)

[2]The segments create a piecewise approximation of the load duration curve and preserve total annual generation and peak load characteristics.

Parameters

δ^t discount factor at time t

Δ_i construction delay of type i (years)

c_i^t capital cost for type i at time t (\$/kW)

f_i^t total dispatch costs for type i at time t (\$/GWh)

τ_j^t duration of segment j at time t (hours)

g_i^t maintenance costs for type i at time t (\$/kW), including grid integration costs

p_s^t economic cost of reduced demand from step s at time t

Given these variables and parameters, the linear cost-minimizing objective function (expressed in million \$) for the deterministic capacity planning problem can be defined as:

$$\sum_t \delta^t \left(\sum_i c_i^t x_i^{t-\Delta_i} + \sum_i \sum_j f_i^t \tau_j^t y_{ij}^t + \sum_i g_i^t w_i^t + \sum_s p_s^t u_s^t \right) \tag{1}$$

Thus, the four primary constituents of total costs are capital costs, dispatch costs,[3] maintenance costs, and costs associated with reduced demand.

All model variants include the following constraints:

- Load balance (market-clearing condition)

$$\sum_i y_{ij}^t - \zeta^t = \tau_j^t \left(d_j^t - \sum_s u_s^t \right) (1 + \alpha^t) \qquad \forall j \in \mathbf{J}, \forall t \in \mathbf{T} \tag{2}$$

  where ζ^t is net international exports at time t, and α^t is a factor that represents a combination of transmission losses and a reserve buffer at time t.

- Capital additions, turnover, and retirement

$$w_i^t = w_i^{t-1} + x_i^{t-\Delta_i} - x_i^{t-L_i} \qquad \forall i \in \mathbf{I}, \forall t \in \mathbf{T} \tag{3}$$

  where L_i is the lifetime of type i.

[3]Dispatch costs for generators are the sum of the variable operation and maintenance costs, fuel costs, and pollutant taxes.

- Unit dispatch cannot exceed capital stock

$$y_{ij}^t \leq a_{ij}^t w_i^t \qquad \forall i \in \mathbf{I}, \forall j \in \mathbf{J}, \forall t \in \mathbf{T} \tag{4}$$

- Cost associated with demand reduction

$$p_s^t = p_0^t (d_j^t)^{-\frac{1}{\varepsilon}} (d_j^t - \frac{1}{n} r_{max} d_j^t s)^{\frac{1}{\varepsilon}} \qquad \forall s \in \mathbf{S}, \forall t \in \mathbf{T} \tag{5}$$

  where r_{max} is the maximum demand reduction (as a percentage of the reference value), n is the total number of steps in the stepwise linear representation of the aggregate demand curve, and ε is the own-price elasticity of demand at the end-use level.[4]

- Investment constraints based on current pipeline or other technological constraints (e.g., no CCS before 2020)

$$x_i^t \leq x_{i,max}^t \qquad \forall i \in \mathbf{I}, \forall t \in \mathbf{T} \tag{6}$$

- Non-Negativity

$$x_i^t, w_i^t, y_{ij}^t, u_s^t \geq 0 \qquad \forall i \in \mathbf{I}, \forall j \in \mathbf{J}, \forall t \in \mathbf{T}, \forall s \in \mathbf{S} \tag{7}$$

Since the electric power sector is entrenched in long-lived and expensive investments, many technical and economic factors can contribute to the retirement of costly generating assets. Retirements occur in the model through three mechanisms. First, retirements can occur endogenously through economic drivers when maintenance costs for units exceed the anticipated economic benefits that such assets bring to the energy system. Second, units that are online at the beginning of the time horizon are likely to be fully depreciated before the end. Such exogenous lifetime constraints for residual capacity are incorporated through a constraint on the percentage of units of a particular type that are online in a given period. Finally, the third mechanism for retirements is when new capacity reaches its operating lifetime during the time horizon of the model run, which also represents an exogenous constraint based on unit lifetimes.

Optional constraints for model runs include climate policy constraints (cap and trade, carbon

[4] This representation is based on Kanudia and Shukla's linear formulation of price-sensitive demand. For a more thorough explanation of this approach, please refer to [19].

tax, or cumulative emissions cap), federal renewable portfolio standards, target wind penetration, constraints on investments for limited technology portfolio runs, and constraints to fix decision variables based on a reference run. The cumulative constraint on greenhouse gas emissions is formulated as:

$$\sum_t \sum_p \gamma_p \left(\sum_i \sum_j e_{ip}^t \tau_j^t y_{ij}^t \right) - \sum_t v^t \leq \phi \tag{8}$$

where p is the index for the greenhouse gas (in this case, CO_2 and CH_4), γ_p is the global-warming potential of p, e_{ip}^t is the emissions factor of technology i for pollutant p at time t (in million metric tons per GWh), and ϕ is the cumulative emission cap (Mt-CO_2e). Emissions offsets can be purchased in lieu of making investments in abatement technologies if cumulative abatement targets cannot be met by reducing emissions (e.g., if the policy target is revealed to be more stringent than initially expected).

3.2 Two-Stage Stochastic Recourse Model

The linear programming model discussed above computes the optimal investment and operation strategies for the deterministic capacity expansion problem. Under perfect information, this solution provides a lower bound on discounted costs given a particular scenario. However, due to the difficulties associated with predicting the outcomes discussed in Section 2 with any degree of certainty, it is unrealistic to assume that a strategy that is optimized for a given scenario will be optimal under a range of realized states of the world. Desregarding inherently random characteristics may limit the usefulness of solutions designed using deterministic approaches.

Stochastic programming techniques can be used to compute optimal hedging strategies in problems with uncertain data and to provide contingency plans that adapt to realizations of random variables. These solutions perform reasonably well under a variety of plausible scenarios. The basic two-stage stochastic program with recourse can be formulated as [20, 21]:

$$
\begin{aligned}
\min \quad z = \quad & c^T x + \mathbb{E}_\xi f^\omega y^\omega \\
\text{s.t.} \quad & Ax \qquad\qquad = b \\
& -B^\omega x + \ D^\omega y^\omega = d^\omega \\
& x, \qquad\quad y^\omega \geq 0, \ \omega \in \Omega
\end{aligned}
$$

$\omega \in \Omega$	state of the world
ξ	random vector, $\xi(\omega)^T = (f(\omega)^T, d(\omega)^T, B_{1\cdot}(\omega), \ldots, B_{n\cdot}(\omega), D_{1\cdot}(\omega), \ldots, D_{n\cdot}(\omega))$
$\Xi \subset \mathbb{R}^n$	support of ξ
x	vector of first-stage decisions
y	vector of second-stage (recourse) decisions

Here, all values corresponding to objective function coefficients (i.e., the c vector) and first-stage[5] constraints (i.e., the A matrix and b vector) are known with certainty. The second-stage objective coefficients (i.e., the f^ω vector) and parameters in the constraints (i.e., the B^ω and D^ω matrices and d^ω vector) are unknown when utilities make first-stage decisions and are characterized only by discrete probability distributions over potential outcomes. The second-stage parameters are treated as random variables with outcomes denoted by ω with an associated probability $p(\omega)$. Every random element depends jointly on these scenarios or states of the world.

The *wait-and-see approach* waits until uncertainties are resolved at the end of the planing horizon (and the outcome $\omega \in \Omega$ can be observed) before selecting the optimal decision vector x. This solution corresponds to a scenario analysis problem (i.e., where uncertainty has been removed and the decision maker solves for different values of ω) and suggests perfect information. The

[5]Stages are distinct from periods in stochastic programming terminology. Periods are intervals in the time horizon. Stages are sets of consecutive periods that divide the time horizon based on realizations of uncertainties and information sets of decision makers.

problem can be formulated as:

$$z^{\omega} = \min\ f(x, \omega)$$
$$\text{s.t. } x \in C^{\omega} \subseteq \mathbb{R}^n$$

with the here-and-now solution expressed as $x^{\omega} \in \text{argmin}\ \{f(x, \omega) \mid x \in C^{\omega}\}$. The expected cost with perfect information can be found by taking the expected value over all possible scenarios: $z_{ws} = \mathbb{E}\, z^{\omega} = \sum_{\omega \in \Omega} z^{\omega} p(\omega)$.

The *here-and-now approach* finds a solution x^* that hedges against all possible contingencies $\omega \in \Omega$ that may occur in the future. This decision is made before observing the outcome from Ω and solves the problem:

$$z^* = \min\ \mathbb{E}_{\xi} f(x, \omega)$$
$$\text{s.t. } x \in C^{\omega} = \cap_{\omega \in \Omega} C^{\omega}$$

where the here-and-now solution is expressed as $x^* \in \text{argmin}\ \{\mathbb{E}_{\xi} f(x, \omega) \mid x \in \cap C^{\omega}\}$. The solution x must be feasible for all scenarios $\omega \in \Omega$. The expected cost of the stochastic solution is $z^* = \min_x \mathbb{E}_{\xi} f(x, \omega)$.

The *expected value approach* replaces the stochastic parameters by their expected values and solves the problem:

$$\hat{z}_d = \min\ f(x, \bar{\omega})$$
$$\text{s.t. } x \in C^{\bar{\omega}}$$

where $\bar{\omega} = \mathbb{E}\omega = \sum_{\omega \in \Omega} \omega p(\omega)$, and the expected value solution is $x_d \in \text{argmin}\ \{f(x, \bar{\omega}) \mid x \in C^{\bar{\omega}}\}$. The expected cost of the expected value solution is $z_d = \mathbb{E}_{\xi} f(x_d, \omega)$.

The importance of uncertainties is typically assessed through two metrics: the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS). The EVPI compares the expected costs of the stochastic and wait-and-see solutions and represents the expected change in the objective function value if perfectly accurate forecasts are available prior to first-stage decisions. The EVPI has important implications for decision makers in that it places an upper bound on willingness to pay for information gathering. The EVPI is mathematically defined as:

$$\begin{aligned}\text{EVPI} &\equiv z^* - z_{ws} \\ &= \min_x \mathbb{E}_\xi f(x, \omega) - \mathbb{E}_\xi \left[\min_x f(x, \omega) \right]\end{aligned}$$

The VSS[6] compares the expected costs of the expected value and stochastic solutions. It quantifies the expected difference in cost for a decision based on stochastic analysis and one that ignores uncertainty. The VSS can guide analysts in the process of model construction by highlighting which uncertainties are most important for inclusion and for more detailed probability elicitations. The VSS can be viewed as the additional expected cost of pretending that uncertainty does not exist, whereas the EVPI is the expected cost of being uncertain. The VSS is defined by the equation:

$$\begin{aligned}\text{VSS} &\equiv z_d - z^* \\ &= \mathbb{E}_\xi f(x_d, \omega) - \min_x \mathbb{E}_\xi f(x, \omega)\end{aligned}$$

Each of these random parameters is assumed to be independent,[7] which means that there are a total of 675 universe scenarios. The model uses a two-stage stochastic programming approach in the GAMS environment using the DECIS system [23] with the CPLEX solver. All uncertainties are assumed to resolve in 2030. From this model period forward, second-stage decisions can be made with complete and perfect knowledge of all future parameters.

[6]The value of the stochastic solution is also called the expected value of including uncertainty [22].

[7]Future research efforts should attempt to more rigorously quantify potential impacts of correlations between random variables. For example, natural gas prices and methane leakage rates may be negatively correlated if low prices provide strong incentives to reduce costs by eliminating control technologies and other practices that could have reduced emissions during well production and completion.

4 Results

4.1 Reference Results

Table 2 lists objective function values[8] for the wait-and-see (z_{ws}), stochastic (z^*), and expected value (z_d) solutions. The top rows list values when the uncertainties are considered one-at-a-time, and the bottom row shows results for all five uncertainties considered jointly.

Table 2: Discounted system costs (billion $)

Uncertainty	z_{ws}	z^*	z_d	**EVPI**	**VSS**
Stringency of abatement policy	3,378	3,486	3,497	108	11
Natural gas prices	3,283	3,286	3,286	3	0
Coal prices	3,304	3,304	3,304	0	0
GWP of methane	3,303	3,303	3,303	0	0
Upstream methane emissions	3,303	3,303	3,303	0	0
Joint	3,358	3,466	3,479	108	12

The expected value of perfect information (EVPI), which presents the difference in expected cost between the stochastic and wait-and-see solutions, is $108 billion.[9] Abatement stringency and natural gas prices account for almost this entire value, and information is most valuable when tight caps are realized. Table 3 demonstrates how, under tight emissions caps, the wait-and-see solution retries considerably more coal and natural gas plants (particularly combined cycle units) early. The 754 GW of total retirements is a large percentage of the US's current installed capacity, which is approximately 1,000 GW. This result demonstrates how very stringent abatement targets require decarbonization of electricity generators almost immediately. Otherwise, it is more costly to implement these reductions down the line, which is why having information about the stringency of abatement is so valuable.

[8]The numerical results in this section should be interpreted within the context of the accompanying model assumptions. Greater emphasis should be placed on the insights gleaned from this framework rather than the exact magnitudes of the model outputs.

[9]All values are expressed in US 2010 dollars with a discount rate of five percent unless otherwise noted.

Table 3: Cumulative retirements by 2030 (GW)

	Wait-and-See[1]	**Stochastic**	**Expected Value**
Coal	311	82	7
Natural gas (combined cycle)	188	111	129
Natural gas (gas turbine)	118	118	118
Natural gas (steam turbine)	75	75	75
Nuclear	5	5	5
Petroleum	57	57	57
Total	*754*	*448*	*392*

[1] Wait-and-see solution for 1,000 Mt-CO_2e per year cap scenario where all other random parameters assume their mean values.

In terms of capacity investments before 2030, the wait-and-see solution under tight caps builds 517 GW of new capacity by 2030 compared to 177 GW under the stochastic solution. The wait-and-see solution constructs more wind (66 GW), more coal with carbon capture (49 GW), and nearly four times as much new nuclear capacity (217 GW) as the stochastic solution.

The value of the stochastic solution (VSS), which quantifies the expected cost difference between the stochastic and expected value solutions, is $12.3 billion, as shown in Table 2. The VSS of zero for the GWP and upstream emissions uncertainties are caused by the fact that there are no first-stage additions of natural gas capacity before 2030 under either of these strategies. There are a number of reasons why the magnitude of the VSS is so small relative to the EVPI. First, utilities and generators do not account for social costs associated with greenhouse gas emissions, which means that the market externality of damages is not included.[10] Second, many of the probability distributions are symmetric, which means that there are both upside and downside risks when adopting the stochastic strategy for most random parameters (e.g., gas prices). Third, most new capacity is not needed until after 2030 to keep up with growing demand. Finally, when uncertainty is ignored in the first stage, it is assumed that utilities will follow the expected value solution.

[10]This assumption and its implications are discussed in Section 4.5.

4.2 Results without First-Stage Mitigation

If the VSS is computed assuming that decision makers do not account for the distribution in climate policy and assume a no policy baseline, the VSS increases to $181 billion, which is much higher than the $12.3 billion value using the expected value solution. This value can be interpreted as the expected cost of inaction. There are two primary reasons for this higher value when no pre-2030 mitigation is assumed. First, the new solution does not make precautionary investments in nuclear or coal with CCS and makes less than optimal installations of wind and biomass. Second, to keep up with growing demand, the no policy strategy builds 106 GW of new supercritical pulverized coal capacity. These would represent large financial losses to utilities if emissions restrictions are later put in place, which would cause these units to be mothballed almost immediately. The magnitude of this no policy VSS value is highly sensitive to the assumed offset price, since first-stage emissions would exceed the cumulative cap.

4.3 2040 Resolution Date

If the uncertainties do not resolve until 2040 (instead of 2030), the VSS increases to $114 billion. This large value results from 30 GW of new nuclear installations by the stochastic strategy in early periods. During this same time, the expected value solution relies on increased generation from coal-fired power plants, as shown in Fig. 2. The EVPI for the postponed resolution date increases from $108 billion to $238 billion. The wait-and-see solution (for tight caps and mean values for other random parameters) builds 386 GW more capacity than the stochastic solution before 2040. In particular, it builds significantly more coal with CCS, nuclear, and wind capacity. The wait-and-see solution simultaneously retires more capacity, including the entire coal fleet and more natural gas combined cycle plants compared with the stochastic solution. Again, these results are sensitive to the offset price, since waiting until 2040 to implement a cumulative abatement policy will involve overshooting the mitigation target.

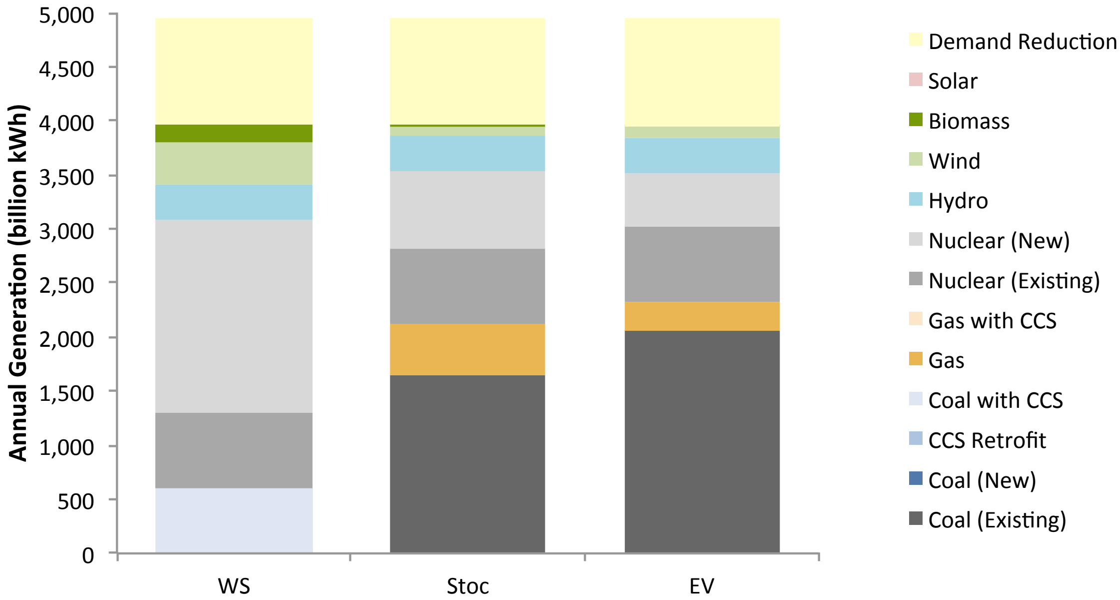

Figure 2: Electricity generation (billion kWh) by technology type in 2030 for wait-and-see (WS), stochastic (Stoc), and expected value (EV) solutions.

4.4 Shale Gas Results

These model runs contain a number of important insights about the potential role of shale gas in the United States. Fig. 3 suggests that shale gas resources are used for electricity generation largely when natural gas prices are low (with abatement targets being a secondary driver). Shale gas and natural gas in general are less important for ambitious climate targets no matter what price is assumed and regardless of upstream emissions. The dark green area in Fig. 3 illustrates that only small amounts of shale gas are used when the natural gas price growth rate is at its mean value or higher. Thus, even though natural gas emits 40 percent less CO_2 per unit mass than coal, these emissions are still too high to merit the use of natural gas to comply with very stringent abatement targets, particularly when wind, nuclear, solar, and other substitutes emit no CO_2.

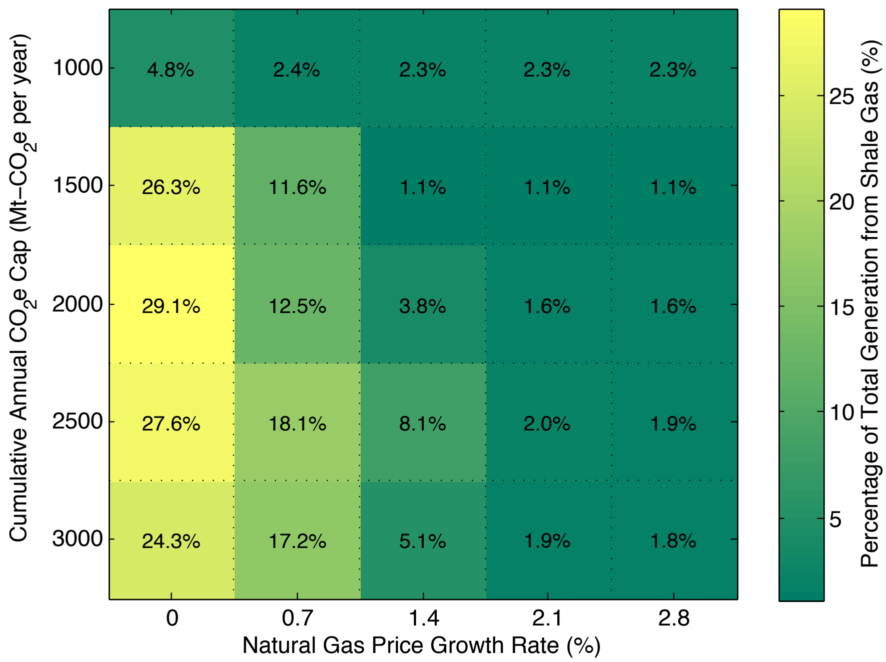

Figure 3: Percentage of total generation after 2010 from shale gas.

A related issue is how shale gas availability will influence investments in renewable technologies. There has been extensive discussion and speculation about the degree to which a low-cost shale boom will curtail the deployment of low-carbon substitutes like wind and solar. The ternary plot[11] in Fig. 4 illustrates that many more considerations than simply the natural gas price will influence how natural gas could displace investments in other technologies.

[11]Ternary plots use barycentric coordinate systems to depict proportions of three variables as locations on an equilateral triangle. The proportions of these three components sum to a constant value (typically 100 percent, as in Fig. 4).

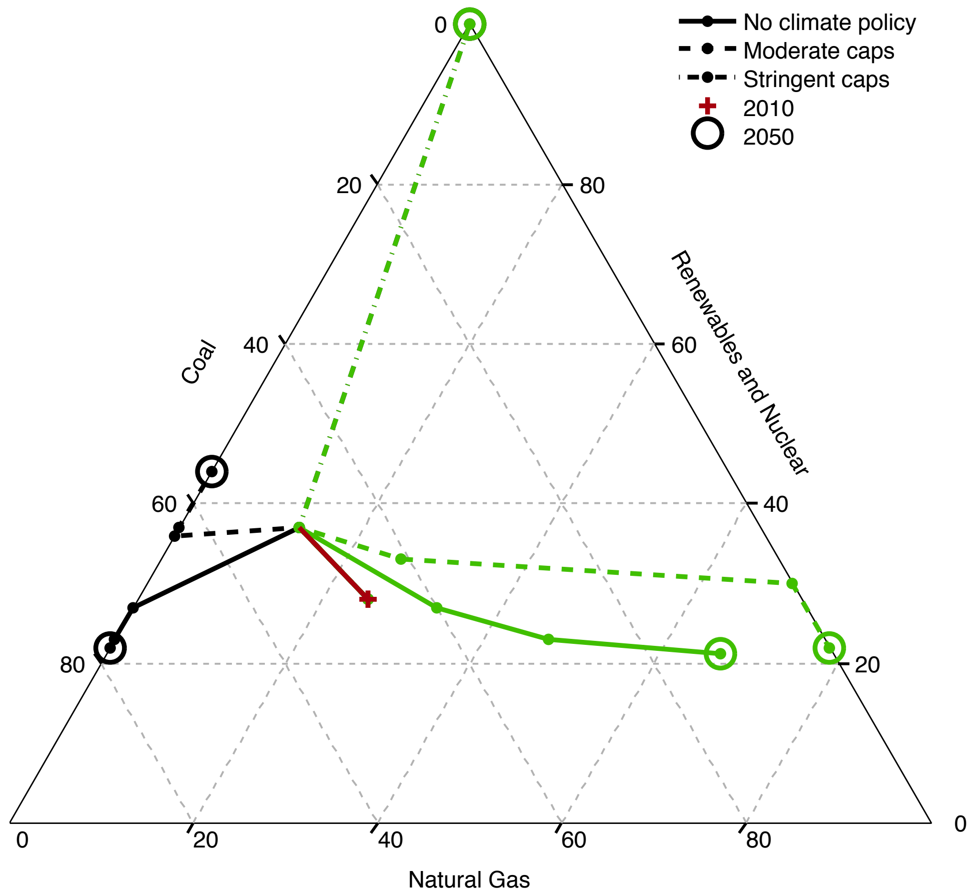

Figure 4: Ternary plot of generation share (%) by technology under various natural gas price and abatement stringency scenarios using the here-and-now (stochastic) approach, 2010–2050. The gridlines indicate the fraction of total electricity generation in a given year from renewables and nuclear (horizontal gridlines), natural gas (diagonal gridlines from the lower left to upper right), and coal (diagonal gridlines from the upper left to lower right). High gas price scenarios are depicted in black and low price scenarios in green with 2010–2020 values shown in red. Note that, since the stochastic hedging approach is used, the strategies are the same for all scenarios before the uncertainty resolution date of 2030. The lines for the high and low gas price cases overlap exactly for the stringent caps scenario.

The expansion of generation from natural-gas-fired units is largest under scenarios where the natural gas price is low and the stringency of climate policy is low to moderate. Under a scenario where no climate policy is enacted by 2030, generation comes primarily from fossil-based units, with natural gas comprising nearly 70 percent of generation by 2050 when gas prices are low. The availability of low-cost shale gas lowers greenhouse gas emissions by replacing production from coal even though no climate policy is in place under this state of the world. When a moderate policy is enacted and abundant shale reserves lower gas prices, coal is eliminated from the generation mix by 2050, and 80 percent of electricity comes from natural gas.[12] For this specific case, the existence of low-cost shale gas means that gas units replace what would have otherwise been predominately coal with CCS (which would generate 26 percent of electricity by 2050), nuclear, and wind. Under a stringent climate policy scenario, however, the presence of shale gas in the resource supply curve for natural gas has almost no influence on the deployment of technologies. The model generates nearly all electricity from non-emitting resources like renewables and nuclear by 2030 regardless of the natural gas price, as shown in the overlapping lines for the stringent cap cases after the uncertainty resolution period. Thus, the influence of shale gas on electric sector investments depends strongly on the stringency of the federal climate policy in addition to natural gas prices.

Another research question with pertinent policy implications concerns how much utilities and generators would be willing to pay for research, development, and deployment of control technologies to limit fugitive methane emissions from shale gas. This value of control places an upper bound on the deployment of control technologies and can be calculated by taking the difference between the expected cost of the stochastic strategy (with all 675 scenarios) and the expected cost of the problem where methane leakage is certain to be zero.

The value of control is $36.3 billion, which indicates that there is considerable benefit to limiting upstream emissions. The reason that control is so valuable is that, for tight abatement scenarios, this strategy allows existing natural gas plants to generate more during the first stage. It relies on extra capacity from less frequently used units (that currently have low capacity factors and are used primarily as peaking plants) instead of building new ones to keep pace with growing demand. The capacity factors in Fig. 5 suggest that utilization of natural gas units in 2020 and 2030 can nearly double if upstream methane emissions are eliminated from shale production, which would allow natural gas units to operate closer to their design capacity.

[12] Since natural gas is still a hydrocarbon, approximately a third of the natural gas generation comes from CCS-equipped units in order to comply with the moderate abatement targets.

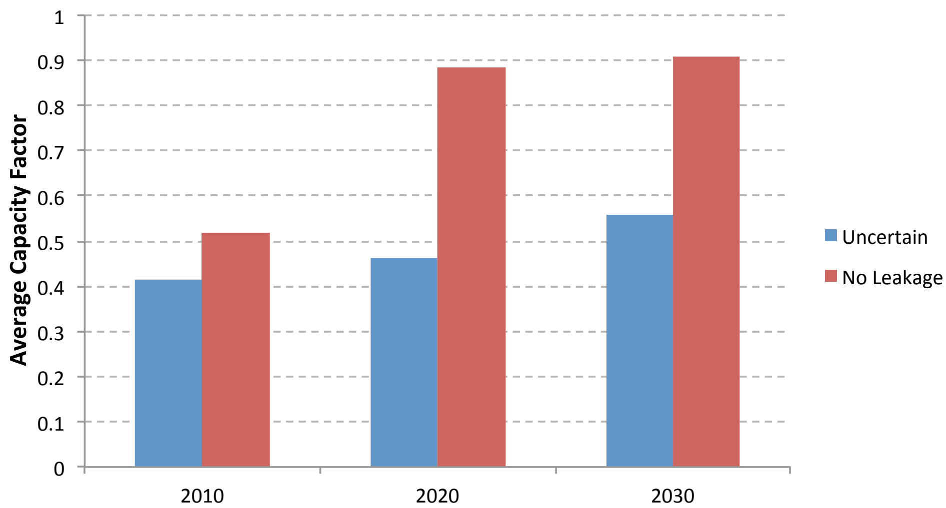

Figure 5: Average annual capacity factor for all natural gas units when the upstream methane emissions from shale production is uncertain versus the control scenario when the leakage rate is zero, 2010–2030.

This control scenario has the flexibility of waiting to observe the resolution of uncertainties in 2030 before building new capacity. It would turn the overbuilding of natural gas combined cycle units from the mid-1990s onward from a liability into a significant asset for reducing system operating costs, CO_2 emissions (until a more certain policy framework is in place), and conventional air pollutants. This strategy would simultaneously maintain grid reliability without additional capital investments. Therefore, limiting methane emissions from shale gas production represents a large value-added proposition for utilities and shale gas developers, since it can allow natural gas to be a holdover technology in a transition to a low-carbon economy.

4.5 Social Cost of Carbon

The results thus far have examined EVPI and VSS values that do not account for damages from greenhouse gas emissions. As mentioned in Section 3, the decision makers in this problem are utilities and generators. Their optimization problem minimizes private system costs without accounting for public social costs. They only consider climate policy targets to be uncertain, even though such policies may not fully internalize the externalities associated with greenhouse gas emissions.

This section explores how these results would change if the so-called social cost of carbon were included in the analysis as an additional cost after model runs. Values for the social cost of carbon over time are uncertain and subject to many assumptions about amplifying feedbacks (e.g., thawing of vast deposits of frozen methane), catastrophic impacts (e.g., slowdown or shutdown of Atlantic Meridional Overturning Circulation), and economic parameters (e.g., social rate of time preference). Therefore, the VSS values are calculated for a range of values and compared to estimates from the literature [24, 25, 26].

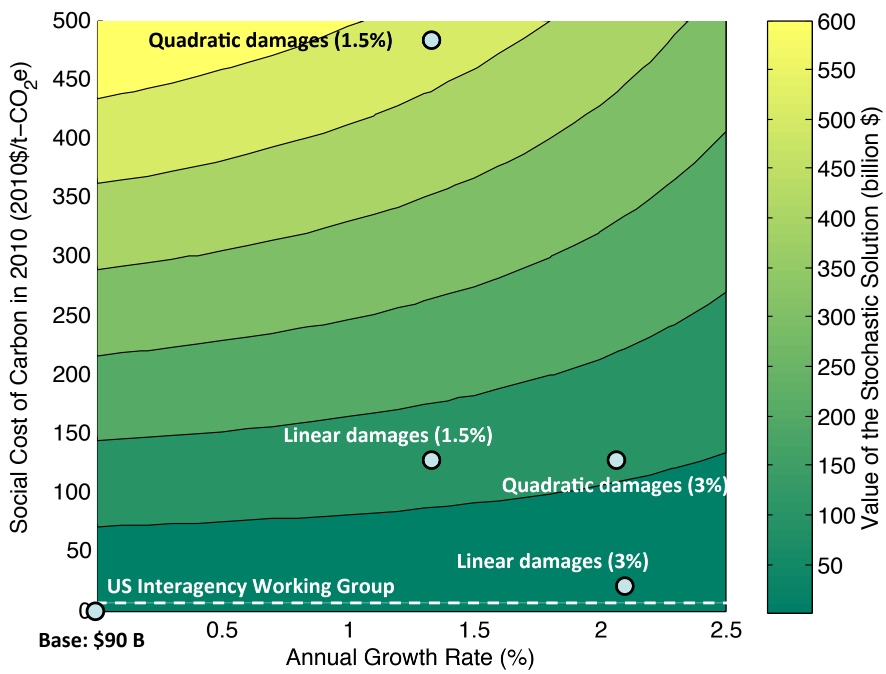

Figure 6: Value of the stochastic solution (billion $) for various social costs of carbon in 2010 and annual growth rates (points on contours show values from the literature with different assumptions about damage functions and discount rates).

Fig. 6 show contours for the VSS at various assumed values for the social cost of carbon in 2010 and annual growth rates over time. The VSS value from Section 4.1 of $12.3 billion (where the social costs of carbon are excluded) is shown at the origin. Including climate damages makes the stochastic solution more valuable, since its precautionary investments in low-carbon technologies and early retirement of carbon-intensive generating capacity mean that it typically has lower first-stage emissions than the expected value solution.

To give a sense of where different analyses fall on the above space, the Obama administration recently announced that benefit-cost analysis of proposed regulations can now include an estimate of damages from greenhouse gas emissions [25]. The value proposed by the US Interagency Working Group is \$14/t-CO_2e, which airs on the conservative side of the literature [24]. One of the largest uncertainties in climate change economics is how economic damages change as global mean surface temperatures increase. Most analyses examine market-based damages at a 2.5 degree Celsius increase over pre-industrial levels and then extrapolate damages at higher temperatures. The linear damage function point on the figure represents a value from Ackerman and Stanton's [24] work, which uses a damage function similar to Nordhaus' in the famous DICE model. However, some economists and physical scientists think positive feedbacks will lead to quadratic damages in temperature. Although the extent of damages is dependent on the exact parameterization of the function, the value from Ackerman and Stanton [24] implies a VSS of over \$100 billion.

Another point of contention is the chosen discount rate for analysis. When dealing with problems of long timescales like climate change, where damages are highly uncertain and may not substantially accrue for many generations, the choice of discount rate in a model becomes as much an ethical, political, and philosophical issue as it is an economic one [27]. Advocates of the descriptive approach to selecting a discount rate contend that an appropriate market interest rate should be chosen (typically 3 percent). However, the prescriptive approach advocates for a lower discount rate of about 1.5 percent.[13] Incorporating the 1.5 percent discount rate increases the social cost of carbon, and in the case of the quadratic damage function, the lower discount rate implies a VSS value of nearly \$600 billion.[14] The VSS value would be even higher if the later resolution date or no pre-2030 policy cases are considered.

[13] If mitigation, like insurance, is most valuable in circumstances that reduce incomes, then the discount rate should be lower than the risk-free rate of return.

[14] There is also uncertainty about the climate sensitivity parameter, which measures how much global temperatures would increase for a doubling in atmospheric CO_2 concentration. The social cost of carbon values when using higher estimates for this parameter are too large to fit onto the chart.

5 Conclusions and Future Work

This research examined how uncertainties associated with shale gas will influence deployment of supply-side technologies in US electricity markets through 2050, particularly in a carbon-constrained world. Although values for metrics like the VSS and EVPI are small for shale gas development relative to the abatement stringency uncertainty, there is considerable value to limiting fugitive methane emissions from shale gas development, which would give the electric sector the flexibility of waiting to observe the resolution of uncertainties before building new capacity. This analysis suggests that utilities and shale gas developers would be willing to pay up to $36.3 billion for the development and deployment of such control technologies.

This result underscores the importance of policies that limit emissions at gas wells. Although there is uncertainty and heterogeneity surrounding the magnitude of methane leaks, this study implies that precautionary investments in control technologies and practices that limit emissions may yield significant economic and environmental benefits. In April 2012, the US Environmental Protection Agency finalized the first set of federal standards for natural gas wells. These rules, which establish National Emission Standards for pollutants like methane and New Source Performance Standards for volatile organic compounds, are a great place to start but a poor place to finish. First, although the EPA rules would make important strides toward reducing the greenhouse gas footprint of shale gas, the standards would not eliminate methane emissions from shale production even if rigorously enforced and may only decrease emissions by one third [28]. Second, the standards do not call for wells to reach full attainment until 2015, requiring producers that postpone implementation to flare emissions until the new equipment is installed. Finally, the rules would not require gas developers to measure or disclose methane emissions data from drilling sites.

The EVPI of $108 billion suggests that information about the stringency of abatement would be particularly valuable when tight caps are realized. This information would allow utilities to retire coal and natural gas units early and begin building more new low-carbon generators like nuclear, wind, and coal with carbon capture. The stochastic solution is especially valuable if no pre-2030 mitigation is assumed, if the uncertainty resolution date is delayed until 2040, or if the social cost of carbon is incorporated into the calculations.

Additionally, model results suggest that the influence of shale gas on electric sector investments depends strongly on the stringency of the federal climate policy as well as on natural gas prices. The shale gas boom will not impede long-term investments in low-carbon technologies like wind if a sufficiently stringent climate policy is enacted in the coming decades. However, if policy makers fail to provide suitable incentives[15] for firms to internalize climate-related externalities, utilities may overinvest in gas-related infrastructure and underinvest in low-carbon technologies relative to their socially optimal levels.

Future research efforts should calculate how the optimal solution changes if the optimization problem were reformulated to make social welfare the objective function (instead of system costs) and if the social cost of carbon were treated as an uncertain parameter (instead of the stringency of climate policy). Comparing the solution of the social planner's problem with the stochastic and expected value solutions for utilities and generators could give important insights regarding the societal and private costs of suboptimal policies, delayed action, and imperfect policy implementation. Given the importance of the abatement policy uncertainty, future work should incorporate a more detailed distribution over abatement stringency to avoid such strong dependence on the offset price. It should also extend the model to include relevant technological uncertainties and conduct more expert elicitations for distributions.

[15] In addition to adopting a climate policy with appropriate levels of timing, stringency, and credibility, establishing proper incentives requires that non-CO_2 gases be included and also that the global-warming potentials for these gases accurately reflect the latest peer-reviewed research. The 2009 Waxman-Markey bill [29] uses a GWP of 25 for methane, which reflects the 100-year timescale value used in the IPCC's Fourth Assessment Report from 2007. Section 2.2 discusses how this value is smaller than the mean value of 33 from Shindell, et al. (2009).

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