Achieving the Clean Power Plan 2030 CO_2 Target with the New Normal in Natural Gas Prices

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ABSTRACT

The U.S. Clean Power Plan (CPP) seeks to reduce CO_2 emissions from electric power by 32% from 2005 levels, in part, by adjusting the generation mix. Generating technologies can substitute via two distinct, but interdependent mechanisms: i) utilization—i.e. adjustment of operations of existing capacity and ii) expansion—i.e. decommissioning and construction of capacity. We develop a framework for analyzing these interdependent mechanisms, then construct and validate an empirical model of the U.S. electricity sector using recent data. Assuming current low gas prices persist, increasing utilization of gas (at the expense of higher-emitting coal) will drive higher returns to gas capacity. As a result, under our business-as-usual scenario for 2030 (no CPP) we project approximately 26% less CO_2 emissions than 2005 levels, indicating that the CPP target could be met with only limited policy intervention.

Keywords: Clean Power Plan, Electricity generation, Carbon emissions, Technology substitution, Capacity utilization, Capacity expansion

https://doi.org/10.5547/01956574.38.5.jpet

INTRODUCTION

The electric power sector plays a pivotal role in economic development (Payne, 2010) and greenhouse gas (GHG) emissions (Williams et al. 2012), making this sector a primary policy target for emission reduction in the United States and around the world. On August 3, 2015, the U.S. Environmental Protection Agency (EPA) announced the Clean Power Plan (CPP) to reduce carbon pollution. The rule promotes flexibility in meeting carbon targets by focusing on emission performance that reflects the "best system of emission reduction" based on three building blocks for supply-side management: improved plant-level (largely coal-fired power) efficiency, switching utilization of existing plants to emphasize less coal and more gas generation, and constructing more renewable power generation capacity (EPA, 2015a). Previous drafts of the CPP rule included a fourth building block: more efficient electricity use. Despite being left off the most recent list of EPA building blocks, end-use efficiency and demand-side management remain an important mechanism for complying with the CPP. Increasing end-use efficiency may have significant potential in offsetting increased total electricity demand (Wang and Brown, 2014). However, the focus of this paper is on endogenous supply-side responses (i.e. capacity utilization and expansion).

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Table 1: The Mapping between the EPA CPP Building Blocks and Mechanisms Determining Changes in Electricity Generation (EPA, 2015a)

	Description from EPA (2015a)	Mechanism
Building Block 1	reducing the carbon intensity of electricity generation by improving the heat rate of existing coal-fired plants	Technical productivity
Building Block 2	substituting increased electricity generation from lower-emitting existing natural gas plants for reduced generation from higher-emitting coal-fired ones	Capacity utilization
Building Block 3	substituting increased electricity generation from new zero-emitting renewable sources (like wind and solar) for reduced generation from existing coal-fired ones	Capacity expansion

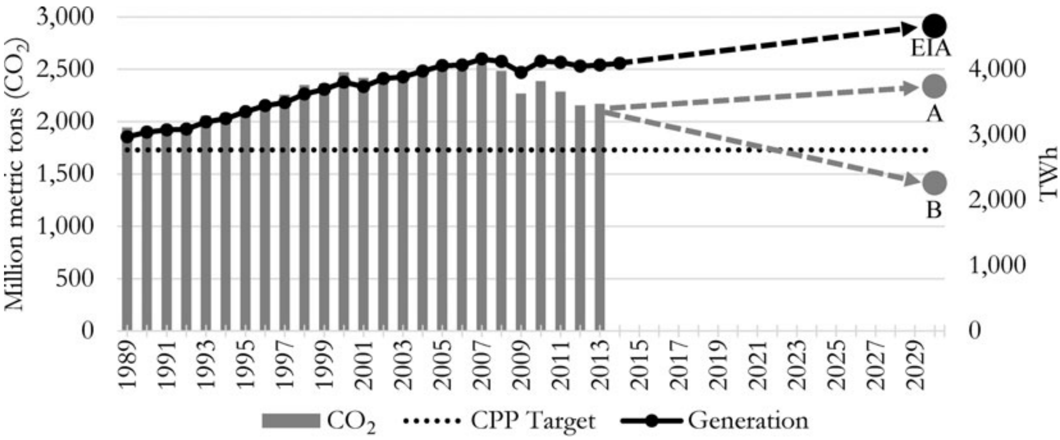
The intent of the CPP rule is to give individual states flexibility to meet state-specific targets. While it is aimed at individual states, the emission target is at the national-level. When fully implemented, the CPP aims to reduce carbon pollution from the U.S. electricity sector by 32.0% below 2005 levels by 2030 (EPA, 2015a). The magnitude and scope of emission reduction policy interventions at present depend on the difference between a business-as-usual (BAU) projection and the CPP target of 32.0% reductions in 2030. If the difference between the BAU projection and the target is small, then the intervention required to meet the target would be expected to be small, and vice versa. Thus, predicting the future evolution of electricity generation is critical for designing appropriate emission reduction policies. This paper provides such an assessment by projecting a BAU scenario starting in 2007 (prior to the shale gas boom) and shifting natural gas prices to 2014 levels. The BAU case describes the technological mix of the electricity sector that might meet 2030 electricity demands and resulting total CO_2 emissions—driven by the decline in gas price, mercury standards, regulatory and resource constraints, and 30% capital subsidies for solar and wind (extended to 2030). Several of these current policies are already driving down sector-wide CO_2 intensity toward the CPP target.

Changes in the level of electricity generation from each technology arise from two distinct economic mechanisms: i) capacity utilization—increases or decreases in operation of existing dispatchable capacity and ii) capacity expansion—construction of new and retiring of old capacity.[1] From the sector-level perspective, utilization is the substitution between *existing* capacities of different technologies in response to prevailing economic conditions, especially fuel prices. This is also termed ‘fuel switching’. Utilization depends on a combination of dispatchability (i.e. the ability to adjust operations, a characteristic of the technology) and technological substitution (i.e. the ability of one technology to replace another, a characteristic of the system). Expansion in a certain technology, on the other hand, is driven by longer-run returns on capital investment. The two mechanisms are interrelated in that returns partly depend on how much generation is produced per unit of capacity (i.e. utilization), and short-term utilization changes may be counterbalanced by long-term expansion. Our aim here is to explicitly represent capacity utilization, expansion, and their interdependency in the face of exogenous perturbations to fuel prices or technology.

In so doing, we make the following contributions to the electric power sector literature. First, using a simple analytical model, we formally characterize the interdependency between capacity utilization and expansion in the generation of electricity—highlighting the role of key parameters in the power sector. If we impose a gas price shock, then in the short-run, because of fixed capacity (i.e. elasticity of capacity supply is zero), capacity returns increase, and the sector quickly

1. Capacity utilization maps to the second and expansion to the third EPA CPP building block shown in Table 1.

Figure 1: Total CO_2 Emissions in the Electricity Sector (left-axis) and Total Generation (right-axis) from 1989—2013



Notes: EIA projection (EIA, 2015a) for total generation in 2030 with associated total emissions using a carbon intensity projection using 1989—2013 data (A) and 2007—2013 data only (B).

adjusts utilization patterns. Returns to capacity are larger when opportunities for gas power (high substitutability and low current generation share) are greater. High returns drive longer-run expansion, but the returns decline with time as the sector expands toward the long-run equilibrium. Second, we extend the analytical model to the U.S. electricity sector and chart a path forward for substantiating models that seek to forecast electricity generation. A corollary contribution is the justification and implementation of an alternate constant elasticity of substitution that ensures input values sum to the output value in the context of electricity (i.e. GWh). Third, using the substantiated model of the U.S. electricity sector, we discuss the magnitude of policies necessary to meet the EPA CPP nationwide target. Driven by the “new normal” in gas prices following the U.S. shale boom and current renewable policies (i.e. mercury regulation and investment subsidies) extended to 2030, electricity sector CO_2 emissions in 2030 may fall by 26.0% compared to the 2005 baseline—just short of the 32.0% CPP target. Therefore, the magnitude of policy intervention needed to meet the CPP target may be much smaller than previous studies suggest.

We begin with a review of the recent decline in CO_2 intensity in the U.S. electric power sector and discuss potential mechanisms which might help explain this trend. After a review of the prevailing classes of economic models used to project electricity generation in section II, section III presents a simplified analytical framework that captures dispatchability, technological substitution, expansion, and their interdependency. This analytical model serves to provide specific insights into how these economic mechanisms interact. Section IV extends the analytical model into an empirical model of the U.S. electricity sector and substantiates the model against historical observations. Section V uses the substantiated model to forecast electricity generation in 2030 and compares to the CPP target. Section VI discusses the implications of the BAU result and concludes.

I. UNDERSTANDING THE DECLINING CO_2 INTENSITY IN THE U.S. ELECTRICITY SECTOR

Sector-wide CO_2 intensity has declined in the U.S. electricity sector since 2007. Figure 1 shows that from 1989 to 2007 sector-wide carbon emissions (vertical bars measured against the left-axis) follows total generation (connected solid dots on the right-axis), indicating a roughly constant sector-wide CO_2 intensity (million metric tons of CO_2 per TWh). However, after 2007 the CO_2 intensity, as well as overall emissions, dropped sharply, as evidenced by the decoupling of generation and total CO_2 emissions in Figure 1. In fact, the level of sector-wide CO_2 emissions observed in 2013 are already 14.6% below the 2005 level, the benchmark year for the CPP target. Furthermore, the wedge between generation and emissions seems to be growing.

For descriptive purposes, we perform a linear regression of CO_2 intensity on time from 1989–2013 which can be extrapolated to 2030 to form a naïve projection of CO_2 intensity. When combined with the U.S. Energy Information Administration (EIA) Annual Energy Outlook (AEO) estimate of total generation in 2030 and their embedded assumptions on end-use efficiency and demand-side evolution, this gives a naïve prediction of total emissions in 2030. Using this simplistic approach, we project total emissions in 2030 to be 8.2% below 2005 levels (Figure 1, point A). However, if we perform a linear regression only over the observations after the decoupling of emissions and generation (i.e. 2007–2013), our projection of total emissions is now 44.5% below 2005 levels, which exceeds the CPP target (Figure 1, point B). Reality likely lies somewhere in between these two naïve projections, and the range reinforces the need for a reliable BAU scenario to 2030.

Obtaining a robust and reliable BAU scenario hinges on understanding the causes of the recent decline in sector-wide CO_2 intensity.[2] We start with the following accounting equation:

$$E_t = \beta_t \cdot q_t^g = \beta_t \cdot (8{,}760 \cdot c_t \cdot q_t^c) \tag{1}$$

where E_t is the total emissions, β_t is the emission rate (per GWh), q_t^g is generation (GWh), 8,760 is the number of hours in a year, c_t is the annual capacity factor, and q_t^c is the capacity (GW) of technology t. Focusing on the percentage change in emissions over the recent past, we can log-linearize [1] to highlight key mechanisms for changing emissions:

$$\hat{E}_t = \hat{\beta}_t + \hat{c}_t + \hat{q}_t^c \tag{2}$$

where the 'hat' accent corresponds to percentage change in the corresponding variable. Recalling the CPP building blocks in Table 1, the three terms on the right-hand side of [2] map to the three distinct mechanisms which impact the sector-wide CO_2 intensity: i) plant-level emission rates, ii) capacity utilization, and iii) capacity expansion, respectively. Utilization plays an important role in determining returns to capacity ($\hat{p}_{kt}$), and the latter, in turn, influences the incentive for expansion. These inter-relationships are illustrated in Figure 2.

We can utilize this framework to better understand the impact of the U.S. shale gas boom. Starting in 2007, the price of gas decoupled from the price of oil and fell dramatically in subsequent years (see Figure 3). This decrease in relative price of gas to coal power (a competing technology) led to increased generation from gas power using existing capacity (Lu, Salovaara, and McElroy, 2012).

Gas power's higher utilization rate increased returns to capacity which, when combined with expectations of coal power emissions regulation, has driven an expansion in gas capacity. Point A in Figure 1 might be thought of as representing the case where all the adjustment in utilization

2. Sector-wide emissions will also depend on total generation. We assume exogenous electricity demand throughout this work (based on EIA AEO projections), focusing instead on the evolution of the supply-side.

Figure 2: A Conceptual Representation of the Capacity Utilization, Expansion, and Their Interdependency

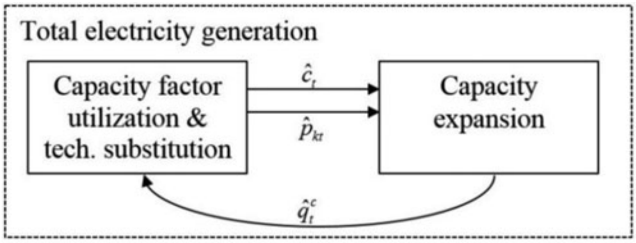
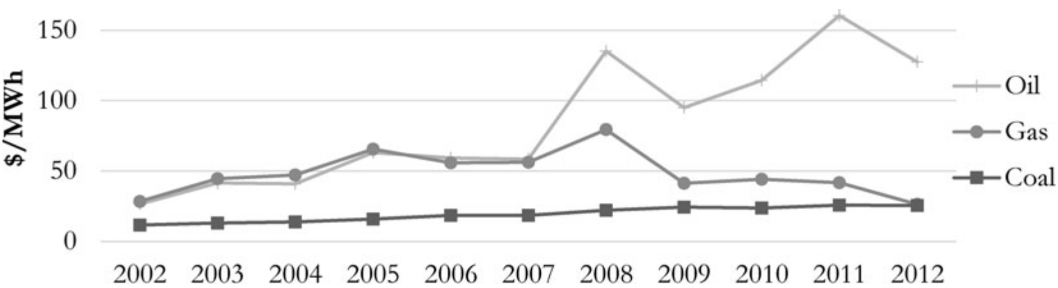


Figure 3: Fuel Prices per MWh of Electricity Produced (nominal US$)



rates has occurred so that the mix in 2013 represents the equilibrium (i.e. does not change further), conditional on existing capacity. However, expansion will likely continue toward 2030 and beyond, indicating that the current generation mix does not reflect a long run equilibrium.

Another driver of expansion over this period were the investment tax credits favoring renewable capacity (primarily solar and wind), which also likely led to a decline in sector-wide emissions. Understanding how these trends may or may not continue in the long-run is critical to creation of a reliable BAU for the 2030 targets. We now turn to a review of models that have been used explore this issue.

II. CLASSES OF MODELS USED TO PROJECT ELECTRICITY GENERATION

There is a large literature offering projections of electricity generation. Here we limit the review to studies after the fall in gas prices (~2009) that report a value for sector-wide CO_2 emissions. Although the numerical value may not affect the conclusions of the particular study, focusing on the reported magnitude allows us to compare methodologies used to construct BAU projections. These studies tend to suffer from some combination of the following three related limitations: i) neglecting the interdependent utilization and expansion mechanisms, ii) assuming equilibrium in the base year, and iii) not substantiating the model against historical observations.

First of all, it is necessary to define and explicitly map utilization and expansion mechanisms in terms of the technology- and sector-level extensive (i.e. number of units) and intensive (i.e. output per unit) margins (see Table 2). Capacity expansion (in GW) maps to the technology-level extensive margin, and total electricity demand (in GWh) maps to the sector-level extensive margin. Capacity utilization covers the entire intensive margin and is based on two determinants:

Table 2: Intensive and Extensive Margins for Electric Power at the Sector-level (top-down) Technology-level (bottom-up)

Perspective	Intensive margin (utilization)	Extensive margin
Sector-level	Technological substitution	Total generation expansion
Technology-level	Capacity dispatchability	Capacity expansion

dispatchability (technology-level intensive margin) and technological substitution (sector-level intensive margin).

There are two primary classes of models that have proved to be useful in making such projections: bottom-up and top-down (Hourcade et al. 2006). Bottom-up models focus on technology-level margins and are useful in incorporating a vast amount of detail including time-varying demand, technological detail, and complex regulations (e.g. loan guarantees, state renewable portfolio standards). Top-down models focus on margins for the sector as a whole and are useful in capturing broader economy-wide changes. However, when viewed through the intensive and extensive margins in Table 2, both classes of models may not completely capture the evolution in generation patterns.[3]

Falling under the bottom-up classification, least cost partial equilibrium optimization models (e.g. Loulou et al. 2004) capture both utilization and expansion, but the least cost objective ignores the link between utilization and expansion (via returns) shown in Figure 2. On the other hand, top-down models (e.g. Paltsev et al. (2005), Sue Wing (2006), Pant (2007), and Château et al. (2014)), both static and dynamic, suffer from comparatively coarse technological detail, and substitution mechanisms in the models do not map directly with the mechanisms described above. For instance, while top-down models may specify both technological substitution and capital expansion, capital does not map precisely to capacity in terms of quantities (GW). If capital does not map to capacity, then technological substitution does not map precisely to utilization (generation per unit of *capacity*, rather than capital). This makes top-down models difficult to calibrate to data; instead, modelers often calibrate to total generation despite the two distinct mechanisms. Imprecise mapping also makes top-down results difficult to communicate for practical purposes.

The second limitation of existing BAU projections is the treatment of the base year of analysis. Bottom-up models are generally calibrated to a single base year (e.g. Bushnell et al. 2014), which, combined with the lack of linkage between utilization and expansion, may ignore ongoing movement towards capacity expansion driven by increased utilization rates. For instance, Burtraw and Woerman (2013) attribute a large reduction in CO_2 intensity to gas-coal substitution, but acknowledge that their BAU scenario does not account for further substitution in the future. Top-down models (e.g. computable general equilibrium (CGE) models) generally assume that the current generation mix is in equilibrium (e.g. Lanz and Rausch, 2011; Cai and Arora, 2015), despite evidence to the contrary (Figure 1). Both classes of models essentially project sector-wide emissions using the current CO_2 intensity and neglect the role of increased utilization rates in driving long-run capacity expansion. As such, we hypothesize that both classes of models likely underestimate the sectoral response to economic shocks, such as the recent gas price decline. In the present context this means that we would expect these models to *underestimate* sector-wide CO_2 emission *reduc-*

3. We do not wish to dismiss the relative merits of other bottom-up and top-down approaches, but rather stress the importance of: i) neglecting the interdependent utilization and expansion mechanisms, ii) assuming equilibrium in the base year, and iii) not substantiating the model against historical observations.

tions in 2030, thereby calling for more stringent policies than necessary to reach the desired CPP target. In fact, we later see this in our results.

Thirdly, because bottom-up model parameters are calibrated to a *single* year and top-down models begin with a snapshot of the *base year* economy in equilibrium, both model classes are rarely substantiated against historical *trends* (DeCanio, 2003). While such a validation exercise[4] may not be necessary for some analyses, substantiating a projection model across several time points can lend confidence regarding the veracity of the numerical results, which are critical for policy design.

The following section outlines a simple analytical model which explicitly and endogenously derives capacity dispatchability, substitution, and expansion, thereby capturing both the intensive and extensive margins of individual technologies and the electricity sector. This simple framework makes clear the limitations of the two model classes described above, and offers insight in what we might expect in the 2030 BAU projections.

III. A SIMPLE ANALYTIC FRAMEWORK

The intent of the simplified model is to explicitly capture the technology- and sector-level intensive and extensive margins (i.e. dispatchability, substitution, expansion, and total electricity demand) to characterize the interaction between the distinct mechanisms that determine changes in electricity generation in response to various stimuli. Box 1 contains the variables and equations for the simple analytical framework.

The first equation in Box 1 (equation [3]), dictates that growth in total electricity demand is driven by exogenous factors $\hat{\delta}^D$ (e.g. population, income) as well as the endogenous price of electricity. The latter response is governed by the own-price demand elasticity, $-\eta^D$. The aggregate power sector is constrained to cover its costs (equation [4]). Derived demands for different technologies in the production of electricity are determined by the total power demand, as well as *technology substitution* at the sector-level intensive margin (equation [5]). The ease with which this can occur is governed by a constant elasticity of substitution (CES) parameter, $\sigma^t \geq 0$. Attributes of the specific electric power system including space, time, and contract lead time prevent perfect substitutability (Hirth et al. 2014). Dispatchability, governed by [7], is represented by a CES parameter depicting the elasticity of substitution *between inputs used to produce electricity* for a given technology, $\sigma_t^i \geq 0$. A non-dispatchable technology is unable to substitute additional operating and maintenance inputs for a fixed capacity (i.e. $\sigma_t^i = 0$), while a dispatchable technology could adjust utilization, as reflected in a positive elasticity of substitution amongst inputs (i.e. $\sigma_t^i > 0$). The scope for capacity expansion in response to a given increase in returns, is given by a technology-specific own-price elasticity of capital supply to that technology, μ_t^s (equation [8]). Note that the sector-level parameters, $-\eta^D$ and σ^t, do not have technology sub-scripts, while the technology-level margin parameters, σ_t^i and μ_t^s, vary across different electricity generation technologies.

A. Total Electricity Demand Shift

With this analytical framework, we are now in a position to explore how the key economic elements of the power system interact. To begin with, we consider the impact of an outward shift

4. The authors recognize that a complete validation is impossible. Substantiation and validation are used interchangeably throughout, and the exercises are meant to lend confidence in the model's numerical results.

Box 1: A simple analytical framework of dispatchability, substitution, and expansion in the electricity sector

(3) $\hat{Q}^g = -\eta^D \hat{P}^g + \hat{\delta}^D$: demand for electricity

(4) $\hat{P}^g = \sum_t \Omega_t^g \hat{p}_t^g$: electricity sector zero profits

(5) $\hat{q}_t^g = \hat{Q}^g - \sigma^t \left(\hat{p}_t^g - \hat{p}^g \right)$: demand for technologies

(6) $\hat{p}_t^g = \sum_i \theta_{it} \hat{p}_{it}$: technology zero profits

(7) $\hat{q}_{it}^D = \hat{q}_t^g - \sigma_t^i \left(\hat{p}_{it} - \hat{p}_t^g \right)$: demand for technology inputs

(8) $\hat{q}_{kt}^S = \mu_t^s \cdot \hat{p}_{kt}$: supply of technology capacity

(9) $\hat{p}_t^g = 0, \ \forall t \neq s$: supply of "other" technologies

(10) $\hat{p}_{it} = 0, \ \forall i \neq k$: supply of non-capital/capacity inputs

<u>Notation</u>: all hat accent variables represent percentage changes in the underlying indexes and capital variables represent total electricity sector variables.

$\hat{Q}^g$, $\hat{q}_t^g$, $\hat{q}_{it}$: % change in total electricity demand, production with technology *t*, and input *i* in *t*

$\hat{P}^g$, $\hat{p}_t^g$, $\hat{p}_{it}$: % change in price of electricity, production with technology *t*, and input *i* in *t*

Ω_t^g, θ_{it} : quantity share of technology *t* in total electricity and value share of input *i* in technology *t*

$\eta^D \geq 0$: own-price elasticity of demand for electricity **(sector-level expansion)**

$\sigma^t \geq 0$: elasticity of substitution between different generation technologies **(substitution)**

$\sigma_t^i \geq 0$: elasticity of substitution between inputs in technology *t* **(dispatchability)**

$\mu_t^s \geq 0$: elasticity of supply for capacity in technology *t* **(expansion)**

$\hat{\delta}_t^D$: ad hoc shifter in total electricity demand

in the total demand for electric power, represented by $\hat{\delta}^D$ in [3]. Equating demand and supply for capacity ([7] and [8], respectively) and solving the model by substituting for price indices and rearranging terms,[5] allows us to see the relationship between the total demand shifter, the extensive and intensive margins, and the returns of capacity, $\hat{p}_{ks}$:

$$\hat{p}_{ks} = \hat{\delta}^D \cdot \frac{1}{\Omega_s^g \theta_{ks} \eta^D + \theta_{ks} \sigma^t (1 - \Omega_s^g) + \sigma_s^i (1 - \theta_{ks}) + \mu_s^s} \tag{11}$$

The denominator of [11] contains four different terms. Each one relates to a different aspect of the power sector's response to increased demand. The larger any one of these terms is, the more dampened will be the response of returns to a given type of generation capacity.

The first term in the denominator represents the electricity demand effect. The more price responsive the consumer demand for power is, the larger this term. This demand-side dampening

5. Online Appendix A shows the complete derivation of this relationship.

effect will be more pronounced, the larger is the share of this type of capacity in total power generation, and the larger is capital's share in the technology in question.

The second term in the denominator of [11] represents the potential for substituting between alternative power generating technologies. For technologies that represent a small share of total capacity, a large elasticity of substitution dampens the change in capital returns for a given demand shock.

The third term in the denominator captures the dispatchability of a particular technology. The higher this elasticity of substitution, the more readily the technology can respond to increased demand (e.g. gas-generated power) and the more damped will be the increase in returns to that type of capacity. We can now see that the returns to capacity is less responsive to the demand shift as technological substitution and dispatchability increase. Dispatchability and technological substitution contribute to the utilization mechanism. If the ability to adjust utilization is high, then the need for expansion is less—reflected by the dampened change in returns to capacity. Alternatively, consider the case where technologies are neither dispatchable nor substitutable (e.g. an electricity system comprising only wind and solar). Returns to capacity would be highly sensitive to demand shocks in this case because the only way to meet the demand growth would be through capacity expansion.

The final term in the denominator of [11] pertains to the elasticity of capacity supply for a given type of generating technology. Not surprisingly, when this is small, as we expect to be the case in the short run, the change in returns to that particular type of capacity, in response to the demand shock, is more pronounced. At the other extreme, if the supply of capital is perfectly elastic, as would only be the case in the very long run, then the denominator becomes infinite and the power sector can adjust its capacity seamlessly to the new demand conditions. This is how a response to fuel price (e.g. gas) can have further consequences to the equilibrium mix of generation over the long-run.

B. Fuel Price Shift

Let us next turn our analysis of the linkages between utilization and expansion to the central issue in this paper, namely the power sector's response to declining natural gas prices. In order to focus the analysis, we assume that only non-fuel inputs (e.g. operating costs) substitute with capacity, so that the price index, given by $\hat{p}_t^v = \sum_{i \in V} \theta_{it}\hat{p}_{it}$, replaces the price index, $\hat{p}_t^g$, in [6] where V is the set of non-fuel inputs, including capacity. Fuel will be treated as an input used in fixed proportion to electricity generation. With these adjustments we can now write the relationship between the exogenously perturbed price of fuel and the returns to capacity as:

$$\hat{p}_{ks} = -\theta_{fs}\hat{p}_{fs} \cdot \frac{\Omega_s^g \eta^D + \sigma^t(1-\Omega_s^g)}{\Omega_s^g \theta_{ks}^v \eta^D + \theta_{ks}^v \sigma^t(1-\Omega_s^g) + \sigma_s^i(1-\theta_{ks}^v) + \mu_s^s} \tag{12}$$

where θ_{ks}^v is the share of capacity cost among other non-fuel input costs comprising set V,θ_{fs} is the cost share of the fuel (e.g. natural gas), $\hat{p}_{fs}$ is the percent change in fuel price for technology s, and the denominator is identical to the denominator in [11].[6] Since all the terms in [12] are non-

6. Online Appendix A shows the complete derivation of this relationship.

negative, we can verify the expected result that a decline in the gas power price due to the fuel price shift (i.e. $\theta_{fs}\hat{p}_{fs} < 0$) will increase the returns to capacity for this particular technology.

Also, the returns from the fuel price shift will be larger as the demand elasticity and technological substitutability increase. The returns to capacity will also be larger as share of natural gas generation in the current mix of generation decreases if the ability to substitute dominates the ability to adjust electricity demand (i.e. $\sigma^t > \eta^D$).[7] These three relationships indicate that returns will be larger when there are greater opportunities to increase market share.

In summary, utilization rates are dependent on final demand, technology, and the composition of the existing electricity system, which can be time-period and region-specific. Furthermore, utilization rates link directly to returns on capacity, which then links to capacity expansion via [8]. Yet these linkages are not present in the bottom-up optimization models that minimize capacity expansion cost, thereby ignoring returns to capacity.

This simple analytical model cannot possibly capture the complexities of the U.S. electricity sector. In the next section we will enrich the framework so we are able to explore, through a series of model simulations, the following questions in the case of the U.S. electricity sector: How did the fuel price decline manifest in the U.S. electricity sector? How will utilization changes affect long-run capacity expansion to 2030?

IV. CAPACITY UTILIZATION AND EXPANSION IN THE U.S. ELECTRICITY SECTOR

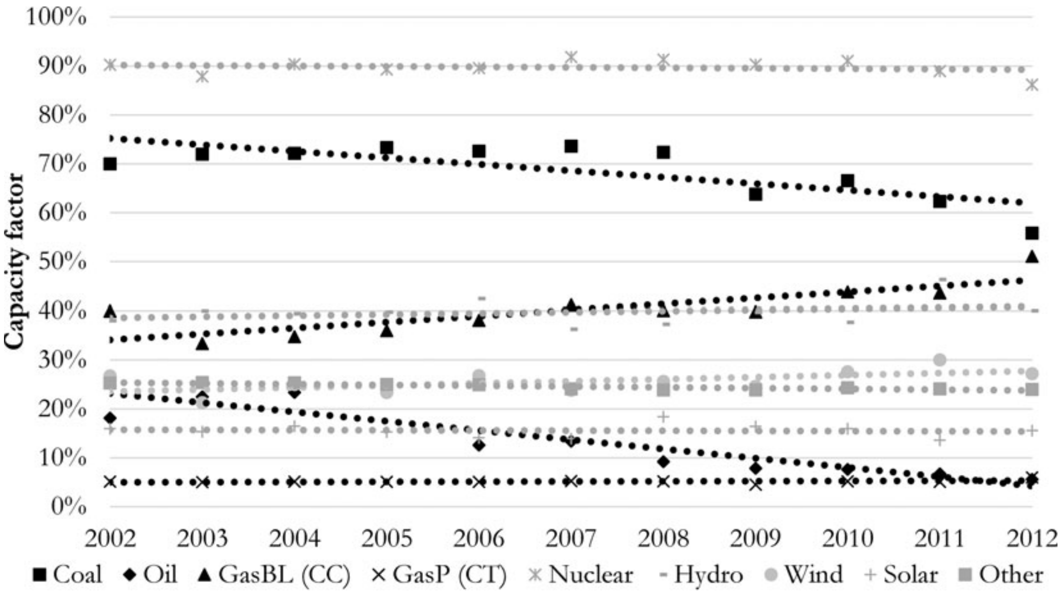
In this section we use data on U.S. electricity production to parameterize an empirical version of the analytical framework discussed in the previous section. The empirical partial equilibrium model described in this section has upward sloping supply curves for all inputs to electricity production (i.e. operating and maintenance (O&M) which includes labor costs, gas, oil, and coal) and downward sloping final electricity demand.[8] Input supplies may be *shifted* to replicate historical observations and or future price projections, but both supply and demand remain price responsive and can capture rebound effects. In this section, ‘one-shot’ shifts to technology, prices, and policies are applied to the 2007 base year, described by the GTAPv8 database (Narayanan et al. 2012), to move the power sector to a new year (i.e. 2007 to 2002, 2007 to 2008, 2007 to 2009, 2007 to 2030, etc.).[9] This results in a series of comparative static results which may be analyzed for historical fidelity or prospective policy purposes. The 2007 base year is an ideal starting point from which to study impacts in the U.S. electricity sector in light of continual expansion driven by utilization from the new normal in gas prices following the shale boom.

7. The derivation of the partial derivatives of these relationships are also in Online Appendix A.

8. Chetty et al. (2011) finds a labor supply elasticity of 0.30, which is used for O&M. Brown (1998) finds long-run supply elasticities of coal and oil to be 1.86 and 0.51, respectively. Long-run supply elasticities for conventional (pre-shale) gas range from 0.4 to 0.8 (Arora, 2014; Ponce and Neumann, 2015; Hausmann and Kellogg, 2015). Instead, we choose 1.2 because Wiggins and Etienne (2015) show an increase in supply elasticity beginning around 2009, which may be due in part to decreasing drill times, pad drilling, and rig mobility, which indicate shale gas might be far more elastic than conventional gas (Coechner, 2010; EIA 2012). Household income is exogenous (i.e. not impacted by electricity prices and tax), and there is no change in international trade. These simplifying assumptions allow for a more controlled analysis and validation of the empirical US electricity sector model.

9. The model described by the non-linear equations in this work are solved using the GEMPACK software (Harrison et al. 2014).

Figure 4: Annual Capacity Factors from 2002–2012 EIA (2015b)



Notes: The slope of the trend line indicates the dispatchability of the technology. Black lines represent dispatchable technologies, while the gray lines represent non-dispatchable technologies. CC is combined-cycle and CT is combustion turbine.

First we introduce the specification for utilization, then capacity expansion. We perform three validations. The first validation focuses on utilization by making capacity expansion exogenous. The latter two validations connect the utilization and expansion specifications in a fully endogenous model of the U.S. electricity sector (as shown in Figure 2) and tests the model's ability to project both total expansion and contributions to total expansion from each technology in response to returns from the utilization portion, respectively. These validations support our specifications for utilization, expansion, and their interdependency in the U.S. electricity sector and lend confidence to the predictive ability of the model.

A. Capacity Utilization

Capacity utilization comprises dispatchability and technological substitution. Dispatchable technologies can be identified by changes in annual capacity factor (Figure 4). In the absence of significant technological change, which could also impact utilization (e.g. efficiency), a dispatchable technology might vary year to year in response to prevailing economic conditions. A non-dispatchable technology cannot adjust utilization. Figure 4 shows that fossil fuel technologies, coal, oil, GasBL (base load), and GasP (peak load) power, are dispatchable, while nuclear, hydroelectric, wind, solar, and other (comprising primarily waste and geothermal) power are non-dispatchable. Some variability may occur in the non-dispatchable technologies due to normal annual operational fluctuations (e.g. plant shutdowns, maintenance); annual rainfall in the case of hydroelectric power; wind in the case of wind power; and sunlight in the case of solar power.

In the production of electricity from each technology, fuel and a capital-O&M composite are assumed to be employed in fixed proportion to power generation from that technology. In the capital-O&M composite nest, non-dispatchable technologies cannot substitute O&M in place of new capital, while dispatchable technologies can vary utilization rates according to a CES parameter (as in [7]).

The second component of capacity utilization pertains to the substitutability of dispatchable technologies in the production of electricity *using existing capacity*. Focusing on the annual utilization in Figure 4, we see that coal and oil utilization declines, while gas utilization increases in response to the decline in gas prices starting in 2009 (recall Figure 3).

Generating technologies are not perfectly substitutable due to factors such as space, time, and contract lead time, especially in a national-level model (Hirth et al. 2014). Supply must equal demand instantaneously in an electricity network. As a result, from the system operator perspective, the values of electricity produced with different generation technologies change over time due to: i) the nature of demand, which can fluctuate by the minute, hour, day, and season, and ii) the operational constraints of technologies that may prevent flexibility in responding to that demand. Figure 5 shows how these features are represented for the production of electricity with existing capacity (i.e. utilization) with a nested additive constant elasticity of substitution (ACES).[10]

We assume that transmission and distribution (T&D) and total generation are always used in fixed proportions. Base type load and peak type load technologies are also demanded in fixed proportions as inputs to total generation. The purpose of the base and peak load distinction is to tease out operational considerations specific to the production of electricity. For example, nuclear and coal power cannot ramp up and down operations quickly and economically in the face of peak demand; therefore, they might substitute with one another, but not as easily with a technology that is better-suited to match peak demand (e.g. gas and oil combustion turbines, GasP and oil). That is, technologies only substitute with technologies of the same load type. Base load technologies are defined as: nuclear, coal, GasBL, hydroelectric, wind, and other; peak load technologies are defined as: GasP, oil, and solar. Total base and total peak are Leontief inputs to generation—i.e. demanded in fixed proportion (assumed 85% and 15%, respectively).[11] The subsequent validation exercises support the usefulness of this specification.

B. Capacity Expansion

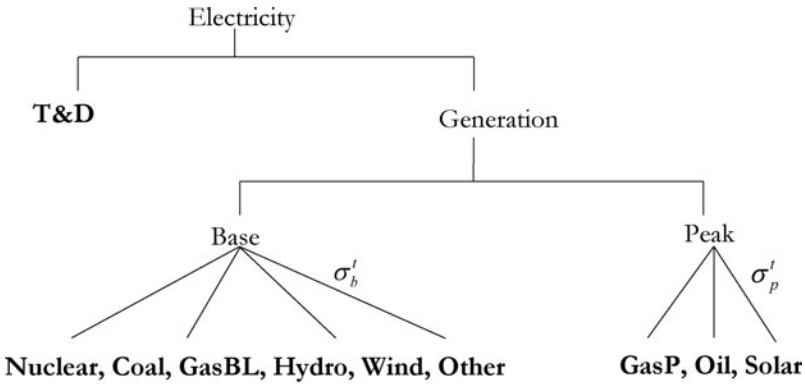
Next, we introduce capacity expansion to respond *endogenously* to returns derived from utilization. It is important to define the difference between nominal (or nameplate) capacity and effective generating capacity. Nominal capacity refers to the actual MW of capacity installed, while effective capacity refers to the capacity that can reasonably be used to provide electricity generation. That is, effective capacity, q_t^e, is simply weighted by the capacity factor ($q_t^e = c_t \cdot q_t^c$). Since generation is what balances supply and demand, effective capacity is important for decision-making in expansion.

The total effective capacity changes can be decomposed into additional and retiring capacity. The rate of nominal retirements are a function of the changes in returns to capacity, $\hat{p}_t^c$, and the annual rate of technical retirements, r_t, which is defined by the inverse of the technical lifetime of each existing technology. Together these two factors capture the "economic lifetime" of the plant

10. Dixon and Rimmer (2006) and Giesecke et al. (2013) implement the ACES specification in the context of labor and land, respectively. van der Mensbrugghe and Peters (2016) compare ACES to the traditional CES formulation. Online Appendix B provides some additional information regarding the theoretical interpretation for electricity production.

11. There are many reasonable substitution specifications (e.g. Paltsev et al. (2005), Sue Wing (2006), Pant (2007), and Château et al. (2014)). The validation exercises in the following section help reinforce the credibility of the one presented in Figure 5.

Figure 5: A Representation of Nested Substitution of Electricity Generation Technologies



Notes: Parameters shown are year-to-year and calibrated over 2002–2012. Model sectors are in bold.

where a plant may extend its lifetime if the rate of return is higher or shorten it if the returns become lower.[12]

$$\hat{q}_t^{cr} = \frac{(100-\hat{p}_{kt})}{100} \cdot r_t \cdot \tau \qquad (13)$$

where $\hat{q}_t^{cr}$ is the percentage change in nominal and effective capacity for technology t due to retirements. The variable τ is the annual time step from the 2007 base year.

Additional effective capacity is the sum of the net effective capacity and total retired effective capacity net of changes in total capacity utilization from all technologies. In levels,

$$Q^g - \sum_t c_t q_t^{oc} = Q^{ea} - \sum_t c_t q_t^{cr} \qquad (14)$$

where Q^{ea} is the required additional effective generation in the sector and q_t^{oc} is only pre-existing capacity such that $\sum_t c_t q_t^{oc}$ is the change in generation resulting from just utilization changes. This accounting condition, with generation terms on the left-hand side and effective capacity terms on the right-hand side, ensures additional capacity meets the generation-based requirements. We can see that, if generation needs and retirements increase with time (and utilization changes to be relatively small), capacity additions will increase with time. Thus, supply elasticity must increase with time.

We can determine the effective capacity additions for each technology according to the following equations:

$$c_t \cdot q_t^{ca} = s_t^a \cdot Q^{ea} \qquad (15)$$

where q_t^{ca} are nominal capacity additions. The coefficient s_t^a is the share of effective capacity additions allocated to each technology t.

12. Data prior to 2014 is given as net capacity changes rather than distinguishing between additions and retirements.

These capacity allocation shares are derived using a multinomial logit (MNL) model where electricity investor's utility U_t is solely a function of the change in rate of return on the capital in technology t, that is $U_t = \alpha \cdot p_t^c$ where the coefficient α, marginal impact on utility from rate of return, is assumed identical across generation types and is calibrated to data. The variable p_t^c is the rate of return on *new* capacity and is linked to rental rates of existing capacity by:

$$p_t^c = a_t \cdot p_{kt} \cdot t_t^c \tag{16}$$

where p_{kt} is rental rate of existing capacity due to change in capacity factor which comes from the capacity utilization portion of the model, a_t is the technological efficiency of new capacity (compared to existing capacity), and t_t^c is the level of capital taxes/subsidies for new capacity.

This specification results in the following equation for s_t^a:

$$s_t^a = \frac{e^{\alpha \cdot P_t^c}}{\sum_t e^{\alpha \cdot P_t^c}} \tag{17}$$

This share determines how much of the total additional capacity need is allocated to each technology in [15]. Thus, net expansion for a technology can be written as:

$$q_t^c = q_t^{ca} - q_t^{cr} \tag{18}$$

The three linkages in the original conceptual diagram in Figure 2 are thus: i) utilization rates influencing returns to capacity ([7] from Box 1), ii) returns to capacity leading to capacity retirements [13] and additions [16], and iii) capacity changes altering utilization rates (returning to [7] from Box 1). The following section integrates these interdependent linkages to test the predictive ability of the complete utilization-expansion model of electric power generation.

C. Threefold Validation

The first validation exercise, termed *utilization-only,* treats capacity changes as *exogenous* (Table 3, first column) and focuses squarely on the utilization mechanism. After this, we let capacity vary in response to the prevailing returns to each generating capacity as determined by utilization. The full *joint utilization-expansion model* (used in both the second and third columns of Table 3) are substantiated against observed and planned capacity additions from 2012—2018.

The purpose of the two joint utilization-expansion validations are to test how the model performs in predicting both total capacity expansion (via [14]) as well as contributions from each generating technology given endogenous changes in capacity rents from capacity utilization (via [17]). That is, first, we project total capacity using a rolling average of previous years of generation projections from the EIA's Annual Energy Outlook (EIA, 2015) (Table 3, second column). Then, we control for total capacity expansion to focus on the contributions from different technologies (Table 3, third column). We show that the model closely matches observations from 2007 to 2018 with expected deviations (i.e. the model fails in predictable ways). Taken together, the three validation exercises contribute confidence to the model's ability to capture utilization, expansion, and their interdependency, and, thus, project a reasonable 2030 BAU scenario, in spite of the fact that the aggregate nature of the model precludes the possibility of some capacity- and region-specific policies (e.g. loan guarantees, state renewable portfolio standards).

Table 3: Exogenous Inputs and Endogenous Outputs for Validation Exercises

	Roadmap for Validation Exercises		
	(1) Utilization-only (2002—2012)	**(2) Joint: total capacity (2008—2018)**	**(3) Joint: tech. mix (2008—2018)**
Growth			
Population	US Census (2002—2012)	US Census (2008—2018)	US Census (2008—2018)
Income per capita	World Bank (2002—2012)	World Bank (2008—2018)	World Bank (2008—2018)
Prices			
Coal	EIA (2002—2012)	EIA (2004—2014)	EIA (2004—2014)
Oil	EIA (2002—2012)	EIA (2004—2014)	EIA (2004—2014)
Gas	EIA (2002—2012)	EIA (2004—2014)	EIA (2004—2014)
Tax	*Various sources*	*Various sources*	*Various sources*
O&M	BLS (2002—2012)	BLS (2008—2018)	BLS (2008—2018)
Utilization			
Total Generation	EIA (2002--2012)	EIA AEO (Rolling average)	Model Output* (2008—2018)
Generation	**Model Output (2002—2012)**	Model Output (2008—2018)	Model Output (2008—2018)
Expansion			
Total expansion	EIA (2002--2012)	**Model Output (2008--2018)**	EIA (2008—2018)
Expansion	EIA (2002--2012)	Model Output (2008—2018)	**Model Output (2008-2018)**

Notes: Exogenous inputs are shaded. The endogenous model output that is validated is in bold.
* Derived by controlling for total capacity.

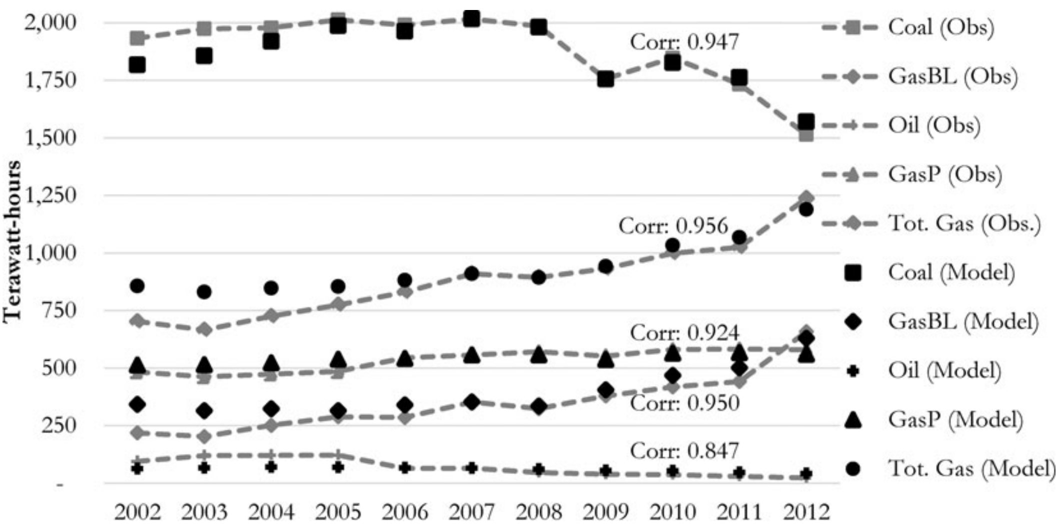
Utilization-only validation

Observed annual capacity factors for generating technologies from 2002–2012 (see Figure 4) are used to calibrate dispatchability and technological substitution parameters for changes in the generation mix arising from the utilization mechanism. We use O&M (with labor (BLS, 2015) as a proxy), fuel (EIA, 2015a), capital (assumed constant), and tax data to construct total generation costs for each technology in the United States from 2002—2012. These data are used to calibrate year-to-year utilization (substitution) parameters for the base and peak load nests (σ_b^t and σ_p^t, respectively).

Using an ordinary least squares estimator, we find an annual elasticity of technological substitution for base and peak load to be 0.462 and 0.472, respectively.[13] These parameters represent year-to-year estimates using observed data; however, for comparing the model results to observations over the medium-term, it is also important to include additional qualitative information that may not appear in the year-to-year quantitative data. Of particular importance are utilities' expectations about coal regulation as well as the shortening of coal contract durations in the wake of the fall in gas prices. The Clean Air Mercury Rule (CAMR) and the Mercury and Air Toxics Standards

13. Online Appendix C expands upon the multi-period calibration.

Figure 6: Utilization-only Validation: A Comparison of Model Results to Observations of Generation from 2002—2012 in the United States



Notes: Observations are dotted gray lines, and model results are black markets and are not connected because they are shifted separately from the 2007 base year. Correlations are next to each technology.

(MATS), issued in 2005 and 2011, respectively, raised expectations for future regulations of mercury and other emissions insofar that several power plants adopted the standards and raised the cost of generation (EIA, 2014). Therefore, we include the estimated costs of these two regulations in the analysis (EPA, 2005; EPA, 2011). Perhaps more impactful, the fall in gas prices beginning in 2009 drove renegotiation and cancellation of long-term coal contracts that were replaced by spot prices (EIA, 2015c). The median duration of coal contract in the United States has been between approximately three and five years (Kozhevnikova and Lange, 2009; Macmillan et al. 2013). If we assume that all coal contracts are three years and expiration is uniformly distributed over those three years, we would expect the year-to-year base load substitutability parameter to increase three-fold over the medium- to long-term. While it is a rough approximation, this reflects the reality that base load utilization is increasingly substitutable due to the cancellation of long-term coal contracts. These two pieces of qualitative information are included in all of the validation exercises as well.[14]

Figure 6 shows that the utilization-only model follows observed results quite well, lending confidence to model's ability to projection capacity utilization in response to prevailing economic conditions.[15]

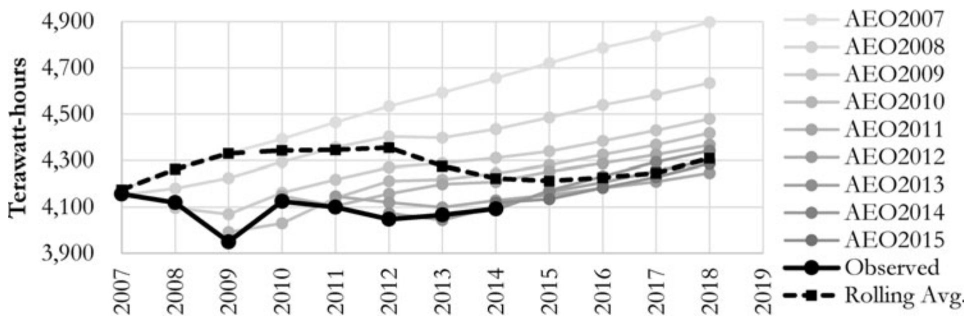
Total capacity expansion validation

Moving to the joint utilization-expansion validations, the foremost difficulty arises from the lag between *planning* period to expected *service* (i.e. lead time) given evolving economic

14. Validation results without these qualitative assumptions are shown in Online Appendix D.

15. The departure from the model and observations from 2002 to 2007 is consistent with a higher impact of mercury and other emissions regulation than the costs we implemented.

Figure 7: Total Capacity Validation: Projections of Total Generation Needs from EIA Annual Energy Outlooks from 2007 to 2015 along with the Observed and a Four-year Rolling Average used as a Projection in the Validation Exercise



conditions over that time period. For instance, Tidball et al. (2010) reports roughly a four-year lead time from the ordering of new capacity to the date of expected service; nuclear and coal lags are likely longer, but neither play a significant role in capacity additions from 2007 to 2018.[16] Unfortunately, in reality, there is no natural experiment which would ensure that the rest of the economy remains constant throughout the construction lead time. This is especially true in light of the economic recession from 2007 to 2009 and the simultaneous decline in gas prices. This is not to say that validation is not possible; instead, validation relies on qualitative discussion of the factors leading to the departures between the model outputs and observations. That is, can we observe that the model fails in expected ways? As in the previous section, model results are based on independent static shifts from the 2007 base year. Nuclear and hydroelectric power are assumed not to expand in the validation, because both are highly constrained by regulations and resource availability, respectively, and do not respond as obviously to strictly economic variables. Capacity expansion results are compared to observed capacity from 2007 to 2013 and planned capacity from 2014 to 2018 (EIA, 2015b).

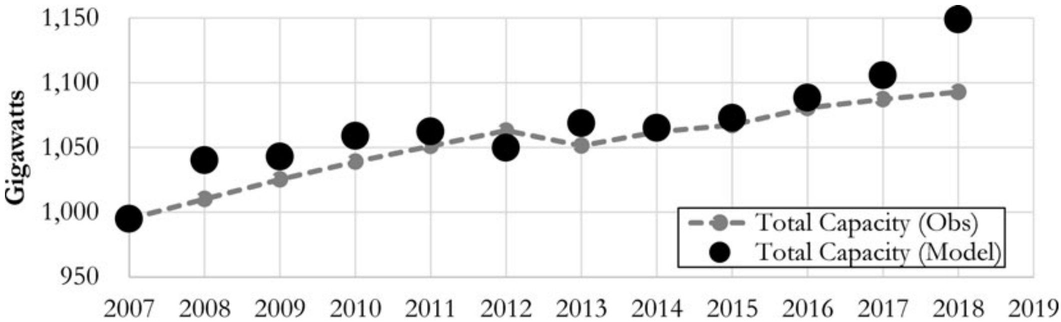
A four-year rolling average of EIA AEO generation predictions are used to endogenously determine total capacity expansion. The intent of using a four-year average for projected generation is to control for differences between what is *planned*, and what actually comes into *service*, which is dependent on factors unfolding during the lead time (e.g. the drop in electricity demand during the economic recession from 2007 to 2009). Figure 7 shows that observed electricity generation was almost always below the EIA AEO predictions.

Because the AEO projections consistently overestimate generation, especially leading into the recession (AEO2007–AEO2009), we would expect the model to also overestimate the actual capacity expansion in the ensuing years, due to the long-term planning horizon. Figure 8 shows that, in fact, the model does overestimate from 2008–2011, as expected.

We also observe some deviation for years 2017 and 2018 in Figure 8. This is due to the fact that planned capacity for 2018 in the EIA data does not account for all the total capacity needs, since it is not necessary to plan four years in advance for some technologies (especially wind and

16. Project lead times vary by technology. Tidball et al. (2010) report an average time from order to expected service of 6 years for nuclear power plants, 4 for coal, 4 for hydroelectric, 2-4 years for gas (depending on technology), 3 for wind, and 2-3 for solar.

Figure 8: Total Capacity Validation: Total Capacity Expansion Projected by the Model Compared to Observations



Notes: Model results for each year are shifted from the 2007 base year. The correlation is 0.908.

solar). Thus, the model fails in an expected way. This validation shows that the model can reasonably predict total capacity expansion over the long-run, given reasonable projections in total electricity generation (which, of course, are elusive in practice).

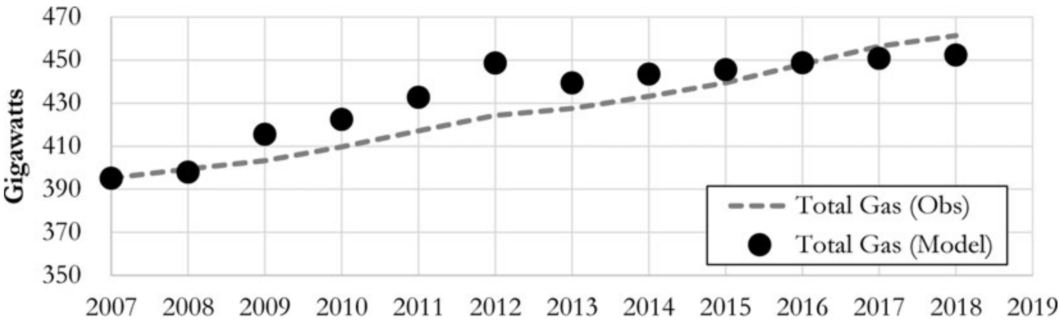
Technology mix in capacity expansion validation

The above confounding factors for validating total capacity expansion demonstrate the need to control for total capacity growth in order to explore the contributions from specific generating technologies. Here, we select shifts in generation which target the observed total capacity expansion—i.e. the model tracks the observations in Figure 8. We then solely focus on how technology-specific capacity expands in response to prevailing economic conditions via utilization, technological change in new capacity, and investment taxes/subsidies.

Here, capacity expansion observed in time τ is based on three driving factors: i) the projection of generation needs that controls for actual total capacity, ii) the technology available at the planning stage (assumed $\tau-4$), and iii) assumed perfect information of input prices at the time of expected service, τ. The second assumption is reasonable because materials must be purchased well in advance of expected service; therefore, the technological efficiency and capital costs of the generating units are prior to service year. Perfect information of future input prices, namely fuel, may be contentious, but this assumption reflects the reality that system operators can cancel and replace capacity contracts in the face of evolving prices after the planning stages but before service. Because of this assumption, we can predict that the model would over-project expansion in gas capacity as well as retirements of coal capacity, because the significant drop in gas prices would not have been predicted by system operators in reality.

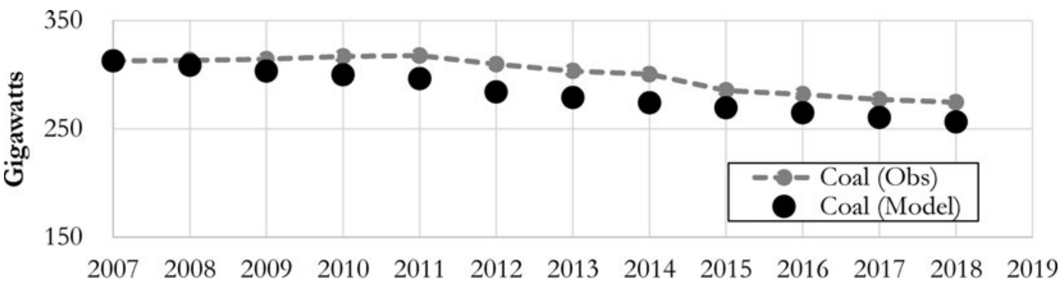
As hypothesized, the assumption of service year input prices leads to an over-prediction of both capacity growth in gas power and retirements in coal power. This is because the model projects capacity expansion given service year prices, while investment decisions would actually be made in the planning years ($\tau-4$) when prices of gas were relatively higher (see Figure 3). Similarly, because gas and coal are highly substitutable (shown in the capacity utilization module) we observe a faster decline in coal capacity using the model (Figure 10). In years after the fall in gas prices the model predictions for gas power and the predictions for the rate of coal retirements

Figure 9: Technology Mix Validation: Gas Capacity Expansion from 2007–2018



Notes: Model results for each year are changes from the 2007 baseline. The correlation is 0.898.

Figure 10: Technology Mix Validation: Coal Capacity Expansion from 2007–2018



Notes: Model results for each year are changes from the 2007 baseline. The correlation is 0.916.

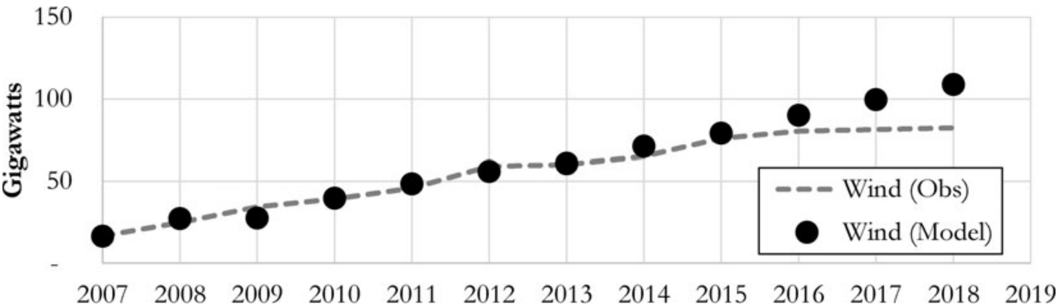
more closely mirror those of the observations.[17] Thus, the model fails in a predictable way which lends support for the validity of the capacity expansion in response to fuel prices.

In addition to the fuel switching shown above, one of the more important trends in the U.S. electricity sector is the expected rise in renewables in response to both technological change and GHG policy. Tremendous growth in both wind and solar over a short time period creates difficulty in projecting with certainty due to a lack of data points. Still, Figure 11 and Figure 12 show the model performs well for both technologies despite the rapid growth observed from 2007 onward.

Addressing DeCanio's (2003) criticism of large-scale energy-economic models, this section presented a detailed representation of the U.S. electricity sector and validates the model's predictive ability against observed data. The independent utilization-only model as well as joint utilization-expansion model are validated against historical trends and appear to perform reasonably

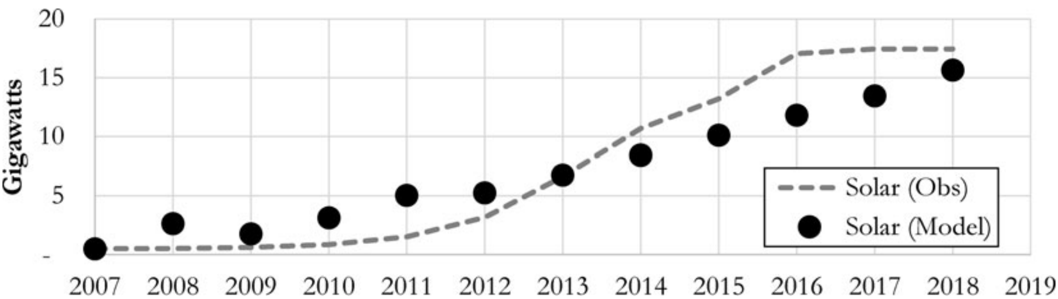
17. Another point to note regarding coal retirements is that they may not respond immediately to economic stimuli. The annual rate of retirements and planned retirements observed in the data from 2007 to 2018 is roughly 1.1% of total capacity which implies an economic lifetime of nearly 90 years, well over their technical lifetime (roughly 60 years), despite decreasing returns to capacity. This is likely due to the fact that many of these plants are already paid off and environmental policies preclude the construction of replacement coal plants. Coal power operators may elect to produce electricity using existing plants as long as possible, even by co-firing with gas or biomass, to avoid costly capacity expansion.

Figure 11: Technology Mix Validation: Wind Capacity Expansion from 2007–2018



Notes: Model results for each year are changes from the 2007 baseline. The correlation is 0.974.

Figure 12: Technology Mix Validation: Solar Capacity Expansion from 2007–2018



Notes: Model results for each year are changes from the 2007 baseline. The correlation is 0.967.

well, supporting the credibility of a BAU projection of future sector-wide emissions using this empirical model.

V. CO_2 EMISSIONS FROM ELECTRIC POWER IN 2030 AND CPP TARGETS

A. A Business-as-usual Scenario for 2030

The BAU scenario projects the U.S. electric power sector to 2030 using projections for total generation needs using the most recent EIA AEO (EIA, 2015a)[18], population (US Census), income per capita (World Bank), and labor costs as a proxy for O&M costs (BLS, 2015). With the exception of large shocks, such as the U.S. economic recession discussed in the previous section, growth rates for these exogenous projections have been historically stable.

Given recent fluctuations in fuel prices resulting from the shale gas boom and the more recent decline in oil prices, steady prices going forward could arguably be a satisfactory assumption. Furthermore, empirical evidence on endogenous technological change suggests that the price of

18. The EIA AEO projections contain embedded assumptions on the evolution of end-use efficiency and demand-side management, which are therefore treated as exogenous in these simulations. This would likely over-estimate total emissions, especially in the case of CPP implementation.

fuels remain fairly constant in real terms over the long-term, albeit with sometimes high year-to-year variability (Stuermer and Schwerhoff, 2013). We also note that, in 2016, gas futures reached an 17-year low (Buurma, 2016), indicating inexpensive gas is expected to stay relatively low. Therefore, fuel prices are shifted to 2014 levels (i.e. a −45.81% shift in real gas price per MMBTU from 2007) to represent the new normal in gas prices. The shifts, as opposed to shocks, maintain the supply response expected from increased gas demand.

Taxes and technology are also shifted to 2014 levels to represent the BAU polices. Current federal investment subsidies for wind and solar (i.e. 30% capital subsidy) are included in the baseline simulation. Because technology is assumed to remain at 2014 levels, the results may be conservative estimates for relatively new technologies (e.g. wind and solar) that are improving at a faster rate than traditional technologies. Furthermore, new coal and oil capacity are assumed to not expand due to regulatory constraints (e.g. mercury and carbon regulations). The economic rate of retirement for coal plants is very difficult to predict in practice. This non-expansion assumption effectively makes net coal power capacity exogenous such that the rate of retirement observed following the fall in gas prices continues at a steady rate to 2030. The retirement decision is notably hard to predict, and there are very few observations against which to calibrate the price responsiveness of retirements. Controlling for coal capacity is well-suited for these BAU simulations because we assume steady gas prices at 2014 levels. However, the exogeneity assumption limits our ability to analyze other gas price scenarios (e.g. a return to pre-shale boom prices).[19] Nuclear and hydroelectric capacity are assumed to not expand due to regulatory and resource constraints, respectively. These BAU policies should drive the result toward the CPP emissions target; although, it is uncertain how and if these might continue in the long-term future.

B. Insights from the Analytical Model

Recall in the simple analytical model we were able to draw several insights about how returns to capacity, and thus capacity expansion, are affected by the gas price shock via model parameters. In the interest of providing a more accurate representation of the U.S. electricity sector, the empirical model introduced a more complex technological substitution (i.e. base and peak nests) and capacity expansion (i.e. discrete choice for additions and economic lifetime for retirements); these add detail to the single elasticity of substitution, σ^t and elasticity of supply of capacity, μ_t^k used in the analytical framework. Furthermore, the simplifying assumptions (e.g. infinite supply elasticity for non-fuel and non-capital inputs) are relaxed and other prices, demands, and technological change are shifted simultaneously.

Still, we can use the response of returns to capacity from the *fuel price shift* from [12], termed X, to add insight into the empirical moving forward.

$$X = \frac{\Omega_s^g \eta^D + \sigma^t(1-\Omega_s^g)}{\Omega_s^g \theta_{ks}^v \eta^D + \theta_{ks}^v \sigma^t(1-\Omega_s^g) + \sigma_s^i(1-\theta_{ks}^v) + \mu_s^s} \tag{19}$$

Table 4 focuses on GasBL where most of the substitution occurs and shows the relevant parameters that comprise X, the gas price shift, utilization, and net capacity expansion for the 2007 base year, 2018 (the last year of the joint validation), and the results for 2030 (discussed in detail later).

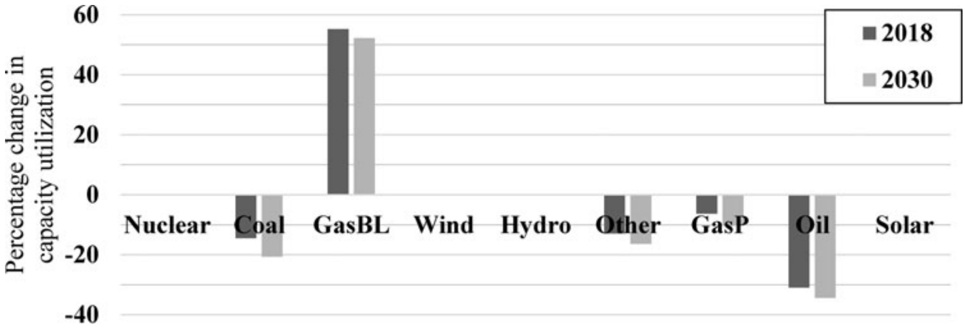
19. Online Appendix E analyzes the sensitivity of this simulation model to gas price and coal power retirement rates.

Table 4: Analytical Model Parameters Relevant for Gas Price Shock Populated with Values from the Empirical Model

GasBL	η^D	θ_{kt}	Ω^{bl}_t	μ^k_t	θ_{ft}	σ^t	σ^i_t	X	$\hat{p}_{ft}$	$\hat{c}_t$	$\hat{q}_c$
2007	0.6	0.125	0.094	0	0.686	1.386	5	0.289	0	0	0
2018	0.6	0.083	0.214	1.45	0.752	1.386	5	0.198	-45.8	55.25	52.05
2030	0.6	0.068	0.218	2.50	0.716	1.386	5	0.168	-45.8	52.24	71.84

Notes: Grayed cells do not change with time.

Figure 13: Percentage Change in Capacity Utilization in 2018 and Extended to 2030

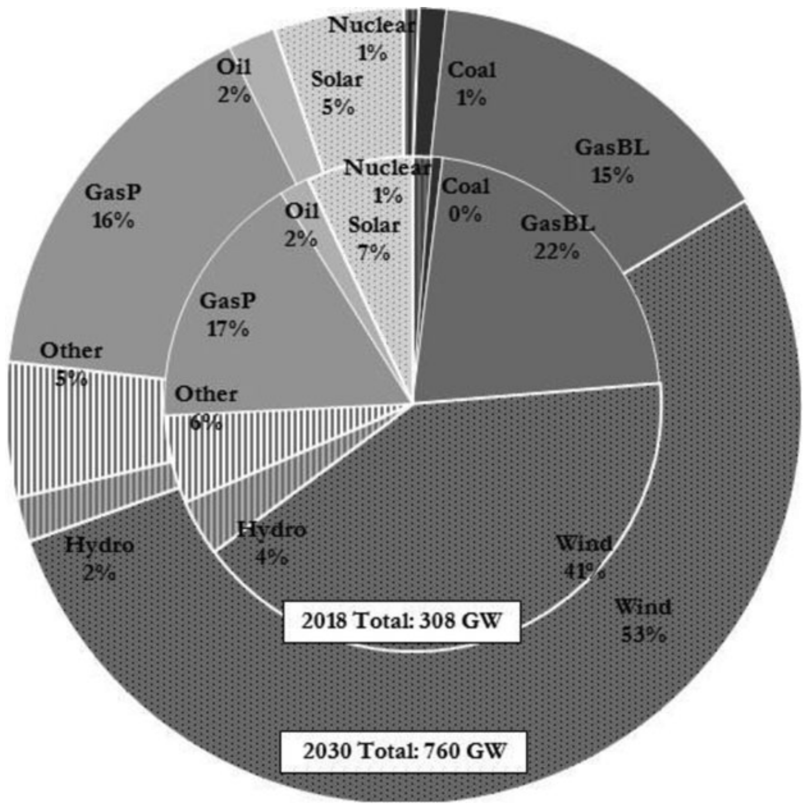


First, we observe that the fuel to capacity ratio, θ_{ft}/θ_{kt}, is increasing over this period, indicating that utilization per unit of capacity is increasing; in fact, $\hat{c}_t$ increases over 55%. In 2030, GasBL utilization increases by over 50% which translates to an increase in capacity factor to from 41% to 62%, surpassing the annual capacity factor of coal plants by 2018. This short-run response stays fairly constant to 2030—depressed only slightly from additional expansion. Second, we note that the elasticity of supply, μ_t^k, increases with time. This is because both total generation needs and total retirements increase with each year from the base year and must be filled with additional capacity; that is, capacity is more elastic over a longer time period. Third, recall that the sensitivity of capacity returns to the gas price shock is based on the ability of gas power to expand (i.e. current market share and ability to substitute). We see tremendous growth in the share of GasBL in base load electricity production, Ω_t^{bl}, increasing from 9.4% to 21.4% in 2018. As a result of this diminished market opportunity (greater generation share) and an increasing supply elasticity, the fuel price response, X, declines about 31% by 2018. This trend continues to 2030; therefore, we would expect capacity expansion from 2018 to 2030 to increase, albeit at a slower rate than from 2007 to 2018 due to a decreasing response. This is what we will observe in the table for GasBL and the following results.

C. Results

Looking back at the validation results, and because we are using the same fuel price shifts as in the validation, it is reasonable to assume that most of the expansion in the 2030 baseline will also come from the gas, solar, and wind. Furthermore, because capacity utilization changes arise from the dispatchability of technologies and the technological substitutability of the sector, which do not change in time, we can hypothesize that capacity utilization in 2030 should roughly match those from validation exercises which use identical fuel prices shifts. Figure 13 shows that the short-

Figure 14: The Shares of Additional Nameplate Capacity for 2007—2018 and for 2007—2030 are Roughly Similar



Notes: Areas to scale.

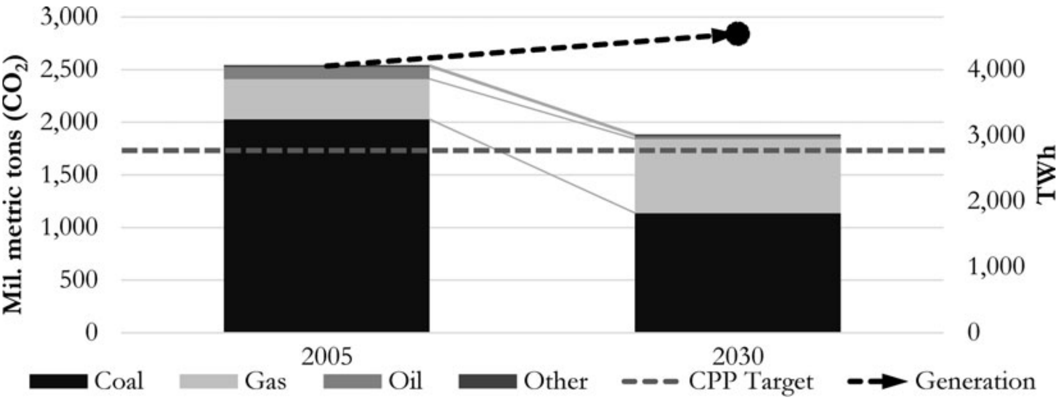
run utilization changes in 2030 are similar to 2018 (the last year of the validation exercises), because of the identical fuel shock and utilization parameters. However, sector-wide utilization declines due to continued expansion in non-dispatchable wind and solar technologies.

Figure 14 shows capacity expansion for each technology. As expected, the rate of capacity expansion for gas power, namely GasBL declines. Wind and solar maintains strong growth due to the investment tax credit that is assumed to remain to 2030. Wind and solar combine for about 20% of total generation in 2030, which pushes down utilization across all dispatchable technologies, shown in Figure 13.

As we observed in the validation exercises in the previous section, there is strong switching from coal power to gas power. Figure 15 shows carbon emissions by source in 2030 compared to 2005. Emissions from coal and oil are reduced by 44% and 59%, respectively, and are partly offset by an 84% increase in emissions from combusting gas. Wind and solar grow to about 20% of total generation, which is large compared to other projections that phase out wind and solar investment subsidies. CO_2 emissions from other power technologies are negligible.

A key driver of the reduction in sector-wide emissions is from changes in coal power utilization and retirements. While the utilization mechanism is fully endogenous and validated in previous sections, coal power retirements are treated exogenously. The rate of retirement is cali-

Figure 15: Contributions to Total CO_2 Emissions by Fuel-type in the United States in 2005 and the BAU Scenario for 2030



brated to observations after the decline in gas prices—providing a reasonable estimate for the BAU simulation undertaken here.[20]

Interestingly, the baseline scenario projects that, with no CPP policies, the CPP goals will almost be met by 2030 under the BAU scenario (26.0% of the 32.0% target). Changes in utilization contributes 11.8% of the total decline in CO_2 emissions while expansion contributes the remaining 14.2%. Only a relatively small remainder must be achieved through further incentives through policy interventions. The equivalent cost of carbon implied by the CPP is only about \$12 per metric ton of CO_2. That is, a tax of \$12 per metric ton of CO_2 is required to meet the full 32.0% target—much less than the social cost of carbon reported by the EPA, which is \$50 per metric ton of CO_2 (based on 3% discount rate average in 2030 in EPA (2015b)). If we impose a \$50 per metric ton of CO_2 tax on top of the BAU assumptions reported above, then the U.S. electricity sector reduces emissions by nearly 48%—both a stricter and more ambitious target.

While the BAU scenario here considers mercury standards, expectations of future coal regulations, 30% capital subsidies for solar and wind, and constant natural gas prices (also up to 2030). Other BAU studies, especially bottom-up models, are capable of integrating a more detailed set of capacity- and region-specific policy (e.g. loan guarantees, state renewable standards). Still, many of the departures in the projections can be attributed to basic modeling assumptions, especially the assumption of equilibrium in the base year.

As expected, the 26.0% reduction projected here is larger than other BAU cases in both bottom-up and top-down literature. Bushnell et al. (2014) use a bottom-up, partial equilibrium model to analyze differences between cap-and-trade and rate-based policies in a handful of western U.S. states. Their BAU case estimates a 10% increase in emissions from 2007–2030 due to increasing demand with the existing technological mix. The partial equilibrium model is calibrated to 2007 and does not consider increasing returns to capacity due to utilization changes, which would drive expansion toward gas and away from coal. The EPA BAU projection used for the regulatory analysis of the CPP is similar, but projects a 17% decline because they begin their analysis in 2013, when the reductions are already 14.6% below the 2005 baseline (as opposed to beginning analysis in 2007 as in Bushnell et al. (2014)). The additional decline in the EPA model seems to be driven by

20. Online Appendix E shows that the results are sensitive to the rate of coal power plant retirements.

assumptions on decreasing renewable costs rather than by additional fuel switching driven from increasing returns to gas capacity. Similarly, the No CPP case in the EIA 2016 Annual Energy Outlook projects a rise in emissions from 2015, where emissions are already 25.6% below 2005 levels, to 23.6% below 2005 levels in 2030, driven by increasing demand with a roughly similar electricity mix.[21] When the (higher) AEO2016 projected gas prices in 2030 are used in the model, along with an appropriately slower retirement rate of coal, the model projects slightly less reduction in emissions, 25.6%. This figure is closer to the EIA AEO2016 results.[22] This sensitivity echoes the need for further research aimed at understanding coal plant retirement decisions in response to returns to capacity, regulation, and fuel prices. Corresponding with the results found in our results, the EIA reports that imposing detailed regulations embedded in the CPP will drive emissions well below the 32.0% target (Martin and Jones, 2016). The EIA analysis also phases-out wind and solar investment credits, whereas the BAU assumes the same credits are extended to 2030. These two points, taken in context of the results shown here, indicate that the CPP may have an even larger impact on emission reduction.

As for top-down models' analyses of the BAU case, Cai and Arora (2015) use a CGE model with several generating technologies which substitute imperfectly, capturing a combined utilization and expansion effect. However, since the model assumes the sector begins in equilibrium, sustained returns in gas capacity expansion are neglected, eliminating any continuity in capacity expansion. The 2030 baseline predicts an 11% decrease in CO_2 emissions from 2005, driven primarily by assumptions on improving technology. Additionally, characteristic of most top-down models, the model does not consider important aspects of electricity production (e.g. base versus peak markets), is not validated, and includes technologies that do not currently exist in meaningful scale (e.g. carbon capture and storage). In both cases, there is little evidence that the current mix of technologies in the production of electricity resembles the equilibrium mix, which the studies generally assume as the starting point. Reductions in emissions in these and other studies are driven primarily by technological change (e.g. declining renewable cost, improving heat rates), whereas the validated model presented here projects a much larger decline in sector-wide emissions driven by increasing returns to gas capacity expansion. This implies that the 26.0% reduction may even be a conservative estimate.

A complete assessment of the relative merits of the different methodologies for modeling the power sector would entail an in-depth model comparison exercise, which is well beyond the scope of the current paper. However, we can conclude that by assuming initial equilibrium, ignoring the continued long-run substitution resulting from increased returns to capacity, and ignoring the interdependency of utilization and expansion of electricity generation capacity, previous studies have likely over-predicted BAU power sector emissions.

VI. CONCLUDING REMARKS

This paper developed a new approach to projecting the power sector's response to today's inexpensive natural gas prices. The analytical model, combined with parameters derived from the

21. The alternate projections of CO_2 emission in 2030 described above are largely based on emissions in the base year, and because of constant reductions in CO_2 emission in the power sector (see Figure 1), the 2030 projections also decrease. Through base year revisions, these projections seem to be converging to the results of the BAU simulation here. The model captures the interdependency between short-term utilization changes toward a longer-term expansion via returns to capacity and could have made the projection shortly after the decline in gas prices rather than constant updates of the base year.

22. Online Appendix E documents this comparison simulation.

empirical study of the U.S. electricity sector, shows that the new normal in gas prices drives substitution to gas power in the short-run by increasing utilization. Increased utilization drives expansion in gas capacity over the long-run due to increasing returns to capacity. However, the rate of expansion slows down as supply elasticity increases and increasing penetration reduces expansion opportunities Overall, the BAU projection to 2030 shows that, given the new normal in gas prices, 26.0% of the CPP target of 32.0% reductions will be met without any additional policy intervention. This result is higher than other studies and may even under-estimate possible reductions, because both end-use efficiency or demand-side management are embedded in the EIA 2030 generation projection which is treated exogenously. As a result, some may conclude that the CPP is, politically-speaking, a 'perfect policy', where achievement of the policy objective requires little enforcement. The alternate perspective would say that the policy objective could be made much stronger. In fact, imposing the EPA's social cost of carbon (i.e. \$50 per metric ton of CO_2), would imply a stricter target of 50% CO_2 reductions in the U.S. electricity sector by 2030 as compared to the 2005 baseline. While this work focuses on contributions to electricity generation from capacity utilization, expansion, and their interdependency, Ang (2004) surveys decomposition methods that could highlight a deeper set of drivers to better inform specific policymaking.

An important limitation of this work is the assumption of a constant economic retirement rate of coal power. Retirements are expected to be sensitive to changes in the returns to capacity, regulations and fuel prices. Future research should focus on developing a better understanding of the determinants of coal plant retirements decisions.

There are also important concerns about achieving the CPP target primarily through gas power. Several articles have shown, and this one supports, that inexpensive natural gas, slows the penetration of renewables (e.g. Shearer et al. 2014). Other studies have shown that the economy-wide life-cycle GHG emissions may not be impacted at all by switching from coal to gas power due to large leakage rates throughout the gas supply chain and potency of gas as a GHG emission (Wigley, 2011; Howarth et al. 2011; Brandt et al. 2014); although, debate remains, especially if fuel switching occurs primarily in electricity as indicated here (Alvarez et al. 2012; Cathles et al. 2012). Thus, if the objective of the policy is to reduce GHG emissions in the United States, rather than just CO_2 in the electricity sector, the BAU projection appears less attractive than on initial inspection.

In closing, there are a number of foreseeable events that could question whether current gas prices are truly a new normal. The first liquefied natural gas exports from the continental United began in early 2016. While still in its infancy, closer integration with global markets may drive up U.S. gas prices and offset some of the shifts shown here. There are also concerns about the steepness of the unconventional gas supply curve. Will inexpensive gas extraction now give way to harder and harder to find shale beds? These could have important impacts on the CPP BAU scenario presented here.

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