Appendix A: Derivations for analytical model

First, we equate demand and supply for capacity (equations [7] and [8] from Box 1)

$$\mu_t^s \cdot \hat{p}_{kt} = \hat{q}_t^g - \sigma_t^i \left(\hat{p}_{kt} - \hat{p}_t^g \right) \tag{A.1}$$

We can substitute [5] for $\hat{q}_t^g$ and subsequently [3] for $\hat{Q}^g$ to construct the following relationship:

$$\mu_t^s \hat{p}_{kt} = -\eta^D \hat{P}^g - \sigma^t \left(\hat{p}_t^g - \hat{p}^g \right) - \sigma_t^i \left(\hat{p}_{kt} - \hat{p}_t^g \right) + \hat{\delta}^D \tag{A.2}$$

With the assumption on supply of inputs in [10] we see from [6] that $\hat{p}_t^g = \theta_{kt} \hat{p}_{kt}$, and with the assumption of supply of "other" technologies in [9] we see from [4] that $\hat{P}^g = \Omega_t^g \theta_{kt} \hat{p}_{kt}$. This allows us to write the above relationship in terms of only $\hat{p}_{kt}$:

$$\mu_t^s \hat{p}_{kt} = -\eta^D \Omega_t^g \theta_{kt} \hat{p}_{kt} - \sigma^t \left(\theta_{kt} \hat{p}_{kt} - \Omega_t^g \theta_{kt} \hat{p}_{kt} \right) - \sigma_t^i \left(\hat{p}_{kt} - \theta_{kt} \hat{p}_{kt} \right) + \hat{\delta}^D \tag{A.3}$$

It is easily shown that by isolating the $\hat{p}_{kt}$ terms and rearranging we return [11]:

$$\hat{p}_{kt} = \hat{\delta}^D \cdot \frac{1}{\Omega_t^g \theta_{kt} \eta^D + \left[\mu_t^s + \theta_{kt} \sigma^t \left(1 - \Omega_t^g \right) \right] + \sigma_t^i \left(1 - \theta_{kt} \right)} \tag{11}$$

Next, let us explore the fuel price shift. Recall that we now assume that non-fuel inputs 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]. Also, the price of fuel ($\hat{p}_{ft}$) is no longer fixed (as in [10]) and is treated as a Leontief (fixed proportions) input to electricity production. Therefore, the price relationships can be written as $\hat{p}_t^g = \theta_{kt} \hat{p}_{kt} + \theta_{ft} \hat{p}_{ft}$ and $\hat{P}^g = \Omega_t^g \theta_{kt} \hat{p}_{kt} + \Omega_t^g \theta_{ft} \hat{p}_{ft}$, where θ_{ft} and $\hat{p}_{ft}$ are the cost share of gas in technology t and the price of gas for technology t, respectively. Starting with Eq. (A.2) we can substitute these new prices to write the relationship in terms of only $\hat{p}_{kt}$ and $\hat{p}_{ft}$:

$$\begin{aligned} \mu_t^s \hat{p}_{kt} = & -\eta^D \Omega_t^g \theta_{kt} \hat{p}_{kt} - \eta^D \Omega_t^g \theta_{ft} \hat{p}_{ft} \\ & - \sigma^t \left(\theta_{kt} \hat{p}_{kt} + \theta_{ft} \hat{p}_{ft} - \Omega_t^g \theta_{kt} \hat{p}_{kt} - \Omega_t^g \theta_{ft} \hat{p}_{ft} \right) \\ & - \sigma_t^i \left(\hat{p}_{kt} - \theta_{kt}^v \hat{p}_{kt} \right) \end{aligned} \tag{A.4}$$

where θ_{kt}^{v} is the cost share of capital in the non-fuel input substitution nest for technology t. Isolating the $\hat{p}_{kt}$ terms on the left-hand side and $\hat{p}_{ft}$ on the right and rearranging allows us to see the relationships shown in [12]:

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

Because the parameters η^D, σ^t, and Ω_t^g appear in both the numerator and the denominator, we must determine the sign of the derivate of the response. Equation [12] can be rewritten as the following.

$$\hat{p}_{kt} = -\theta_{ft}\hat{p}_{kt} \cdot \frac{\alpha x + a}{\beta x + b} \tag{A.5}$$

where x is the parameter we want to explore by taking the partial derivative of $\hat{p}_{kt}$ with respect to x. Following the quotient rule, the partial derivative can be written as:

$$\frac{\partial \hat{p}_{kt}}{\partial x} = -\theta_{ft}\hat{p}_{kt} \cdot \frac{\left(\beta x + b\right)\alpha - \left(\alpha x + a\right)\beta}{\left(\beta x + b\right)^2} = -\theta_{ft}\hat{p}_{kt} \cdot \frac{\alpha b - \beta a}{\left(\beta x + b\right)^2} \tag{A.6}$$

Here, we can focus on the sign of $\alpha b - \beta a$ because the denominator must be positive.

First, let us explore the sign of $\frac{\partial \hat{p}_{kt}}{\partial \eta^D}$. For η^D: $\alpha = \Omega_t^g$, $a = \sigma^t(1-\Omega_t^g)$, $\beta = \Omega_t^g \theta_{kt}^v$, and $b = \theta_{kt}^v \sigma^t (1-\Omega_t^g) + \sigma_t^i (1-\theta_{kt}^v) + \mu_t^s$, which results in:

$$\alpha b - \beta a = \Omega_t^g \sigma_t^i (1-\theta_{kt}^v) + \Omega_t^g \mu_t^s \geq 0 \Rightarrow \frac{\partial \hat{p}_{kt}}{\partial \eta^D} \geq 0 \text{ for a decline in gas price.}$$

Next, let us explore the sign of $\frac{\partial \hat{p}_{kt}}{\partial \sigma^t}$. For σ^t: $\alpha = (1-\Omega_t^g)$, $a = \Omega_t^g \eta^D$, $\beta = \theta_{kt}^v (1-\Omega_t^g)$, and $b = \Omega_t^g \theta_{kt}^v \eta^D + \sigma_t^i (1-\theta_{kt}^v) + \mu_t^s$, which results in:

$$\alpha b - \beta a = (1-\Omega_t^g)\sigma_t^i (1-\theta_{kt}^v) + (1-\Omega_t^g)\mu_t^s \geq 0 \Rightarrow \frac{\partial \hat{p}_{kt}}{\partial \sigma^t} \geq 0 \text{ for a decline in gas price.}$$

Higher technological substitution implies higher returns.

Finally, let us explore the sign of $\frac{\partial \hat{p}_{kt}}{\partial \Omega_t^g}$. For Ω_t^g : $\alpha = \eta^D - \sigma^t$, $a = \sigma^t$, $\beta = \theta_{kt}^v \left(\eta^D - \sigma^t\right)$, and $b = \theta_{kt}^v \sigma^t + \sigma_t^i (1 - \theta_{kt}^v) + \mu_t^s$, which results in:

$$\alpha b - \beta a = \left(\eta^D - \sigma^t\right) \sigma_t^i (1 - \theta_{kt}^v) + \left(\eta^D - \sigma^t\right) \mu_t^s$$

Therefore, $\frac{\partial \hat{p}_{kt}}{\partial \Omega_t^g} \geq 0, \quad \eta^D > \sigma^t$ and $\frac{\partial \hat{p}_{kt}}{\partial \Omega_t^g} \leq 0, \quad \sigma^t > \eta^D$ for a decline in gas price. In the model presented in this work $\sigma^t > \eta^D$, and the response in returns to capacity from the fuel price shift increases with a small current share of generation from technology t.

Appendix B: Justification and comments on additive CES in electricity

While it may be intuitive to think of the system operator problem in terms of cost minimization, the average cost of producing electricity is an incomplete idea in that it does not reflect the complete cost to the system operator because of costs incurred by operational constraints, which can be quite large and are difficult to identify and incorporate into market-derived prices. For instance, the Pennsylvania-New Jersey-Maryland (PJM) market identifies additional costs, such as day-ahead and balancing operating reserves, reactive services, synchronous condensing, and black start services. The purpose of identifying and categorizing these costs is "to reflect the impact of physical constraints in market prices to the maximum extent possible (Monitoring Analytics, 2015, pg. 144)" mainly to ensure *reliability* of instantaneously adjusting supply (and having reserves) to meet unpredictable demand (Monitoring Analytics, 2015).

Recognizing that average costs of generation are incomplete, there is an unobserved *utility of supply* that reflects the usefulness of the supply from different technologies in meeting the specific nature of the demand. This utility of supply balances average cost of generation, reliability costs, and costs incurred from operational constraints in the face of supply and demand uncertainty.

Therefore, we pose the system operator problem for utilizing existing capacity as having two components. First, the operator maximizes the utility of the supply where the utility is defined as a CES function with inputs given by the revenue obtained from each generation technology. That is, the system operator gets some positive contribution to overall utility from revenue obtained from certain technologies. Here, revenues, rather than the technologies, are substitutable. The second part of the utilization problem requires that the summation of the supply of electricity production from each generating technology, q_t^g , must meet the total electricity demand, Q^g . This quantity constraint ensures that the sum of the inputs (i.e. production from individual technologies) is equal to the total output (i.e. total electricity production), which is not the case in the traditional CES framework. The capacity utilization problem can then be constructed as:

$$\max_{q_t^g} U = \left[\sum_t \left(p_t^g \cdot q_t^g \right)^{\rho} \right]^{\frac{1}{\rho}} \tag{B.1}$$

subject to:

$$Q^g = \sum_t q_t^g \tag{B.2}$$

where U is the utility of supply of electricity, p_t^g is the level revenue per unit of electricity generated from technology *t*, q_t^g is the level of production using technology *t*, and Q^g is the total electricity demand. The substitution parameter, σ^t, is given by $\sigma^t = 1/(1-\rho)$. Here, the observed mix of revenue from various electricity generating technologies is the mix which optimally satisfies the complex nature of demand given by the unobserved utility of supply.

Dixon and Rimmer (2006) show that the log-linearized version, as in Box 1, of this expression can be written as:

$$\hat{q}_t^g = \hat{Q}^g - \sigma^t \cdot \left(\hat{p}_t^g - \sum_{s \in T} \Omega_s^g \hat{p}_s^g \right) \tag{B.3}$$

where T is the set of generating technologies, and Ω_s^g is the share of generation from technology *s* in terms of volume (GWh) as opposed to value (US$) as would be the case in the traditional CES construction. Perfect substitution, $\sigma^t = \infty$, would imply that a small increase in revenue from a specific technology would result in all electricity being produced by that technology. Leontief, $\sigma^t = 0$, implies that the same proportion of revenue must always come from a given technology. We apply this alternative CES concept to the substitution of utilization – that is q_t^g is replaced by capacity utilization, c_t.

Appendix C: Calibrating the elasticity of technological substitution for the base and peak load nests

The elasticities of technological substitution are estimated for the base and peak load nests shown in Figure 5 using equations C.1 and C.2 below, respectively, where the percentage change variables are for annual time steps starting with 2002 and ending with 2012. That is, *n*=1 is the percentage change from 2002 to 2003, *n*=2 is the percentage change from 2003 to 2004, and so on. There are 10 observations in total.

$$\hat{q}_{tn}^{g} = \hat{Q}_{n}^{g} - \sigma_{b}^{t} \cdot \left(\hat{p}_{tn}^{g} - \sum_{s \in B} \Omega_{sn}^{b} \hat{p}_{sn}^{g} \right) + \varepsilon_{tn}^{b} \quad for\ \forall t \in B \tag{C.1}$$

$$\hat{q}_{tn}^{g} = \hat{Q}_{n}^{g} - \sigma_{p}^{t} \cdot \left(\hat{p}_{tn}^{g} - \sum_{s \in P} \Omega_{sn}^{p} \hat{p}_{sn}^{g} \right) + \varepsilon_{tn}^{p} \quad for\ \forall t \in P \tag{C.2}$$

where *B* and *P* are the sets of base and peak load technologies, respectively, and the index n represents the observation for annual percentage change. The error terms of error terms, ε_{tn}^{b} and ε_{tn}^{p}, represent the deviation of the observed and the CES specification for base and peak load for each technology and annual percentage change observation, respectively.

Here, the relevant data are annual generation for each technology, q_t^g , and annual costs of generation by technology, p_t^g. The variable Q^g can be constructed by summing q_t^g across all technologies for the year in question, and Ω_s^b and Ω_s^p are constructed by share-weighting q_t^g over the B and P sets, respectively. EIA (2014) has annual data on q_t^g from 2002 to 2012.

Annual percent change in costs of generation by technology are constructed from the following equation:

$$\hat{p}_{tn}^{g} = \sum_{i} \theta_{it} \hat{p}_{itn} \tag{C.3}$$

where θ_{it} is the share of the cost of input i (i.e. fuel, O&M, and capital) in producing using technology t, and $\hat{p}_{itn}$ is the percentage change in price of input i in technology t for annual time step n. Cost shares of inputs in each technology are taken from the initial CGE database (Peters, 2015). Annual values for p_{it} are required for each technology to determine p_t^g. BLS (2015) has data on labor costs in the total electric power sector, and changes are applied across all technologies uniformly; the impact on total price of generation will depend on the share of O&M in the cost structure of the particular technology. Fuel prices for coal, oil , and gas (measured in real price per MMBTu observed in the electricity sector) are also available from EIA (2014) from the relevant time period. Capital costs are assumed to have no change since we are investigating short-term changes in generation from factor utilization only (p_{kt}). Moving from annual level variables to annual percentage change variables is straightforward.

The elasticities of technological substitution σ_b^t and σ_p^t are chosen such that they minimize the sum of error terms, ε_{tn}^b and ε_{tn}^p, across observations and technology -- akin to an OLS estimator:

$$\min_{\sigma_b^t, \sigma_p^t} \sum_n \sum_{t \in b} \varepsilon_{tn}^b + \sum_n \sum_{t \in p} \varepsilon_{tn}^p \tag{C.4}$$

The resulting QCES parameters for base and peak load technology substitution are 0.462 and 0.472, respectively. T-statistics on the parameters show that these cannot be said to be significantly different than zero, presumably because of the lack of data (i.e. only 10 observations). As econometric work, this is probably seen as unsatisfactory; however, CGE takes the perspective that prices and quantities are endogenously determined, as opposed to exogenous prices in this estimation, and the greater concern are the feedbacks in the structure of the economy. More observations would be required to be certain of the "true" parameter value.

Of greater interest than the significance of the parameter values is how well these parameter values characterize factor utilization in the economic model, shown in the validation section of this work.

Appendix D: Utilization-only validation without qualitative adjustments

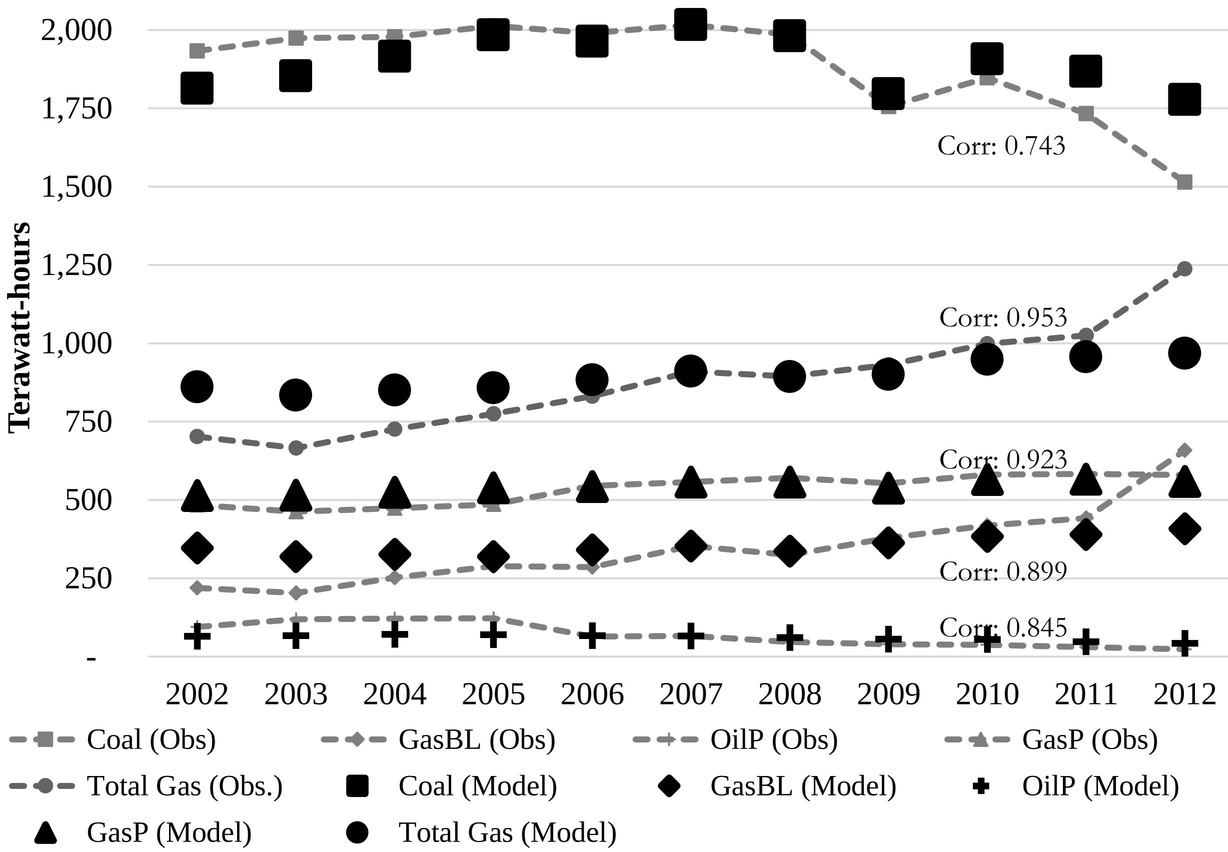

Figure D.11: Utilization-only: A comparison of model results to observations of generation from 2002—2012 in the United States. Observations are dotted gray lines, and model results are black markets and are not connected because they are shifted separately from the 2007 base year. Correlation values are next to each technology. Year-to-year, unadjusted parameter for base load nest (σ_b^t = 0.462 and σ_p^t = 0.472).

Appendix E. Systematic Sensitivity Analysis of natural gas price on total CO_2 emissions.

Two of the key drivers of the simulation results are the price of natural gas and the rate of coal power retirements. This appendix provides insight on the sensitivity of our results to the assumptions made in this article.

While the intent of the work is to project a BAU case with the "new normal" assumption about the price of natural gas (i.e. a permanent shift to 2014 levels), it is worthwhile to test the sensitivity of the simulation results to this assumption. Given the sharp decline in gas price following the shale boom, we are uncertain about the nature of uncertainty in future gas prices. Therefore, we make simple assumptions on gas prices to inform the sensitivity analysis. In terms of annual costs of natural gas to the electricity sector, the minimum cost of natural gas was $3.09 per MMBTU in 2012 (all prices are in 2007 dollars - i.e. the base year of the model). The price used in the analysis to project emissions in 2030 is $3.85 from 2014, while the EIA anticipates a higher price in 2030: $4.87. For the sensitivity analysis we postulate a triangular distribution of uncertain gas prices wherein our price assumption and the EIA assumption are equally likely with the mean of this symmetric distribution being placed at the average of these two prices. The minimum price is set at the 2012 price level and maximum price is set equally far from the mean (i.e. $5.64). Figure E.1 shows this distribution.

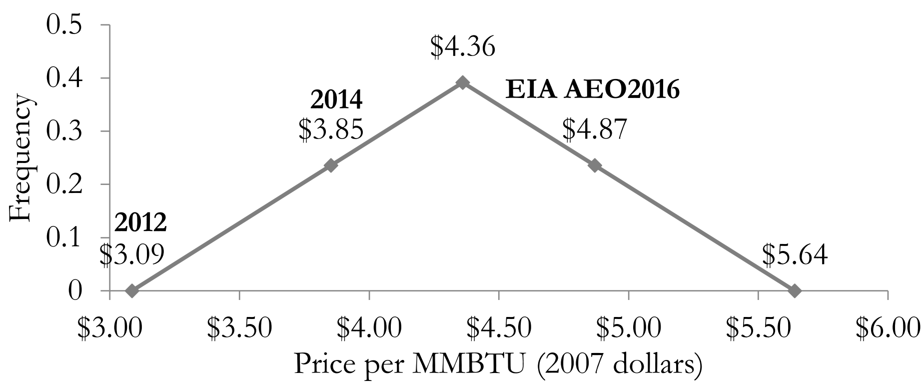

Figure E.1. Triangle distribution of natural gas prices for sensitivity analysis.

Second, the rate of coal power retirements was calibrated to the rate of retirement observed following the decline in gas prices following the shale boom, matching the BAU simulation assumptions. We do not believe there are enough observations to draw conclusions regarding the price responsiveness of coal retirements in the new economic environment; that is, we can only be confident of the rate of retirements with the "new normal" price assumption described in the article (i.e. a shift to 2014 levels). Still, it is worthwhile to test alternate assumptions of the rate of retirements, also, using a triangle distribution. Tidball et al. (2010) reports a 60-year technical lifetime for coal plants. Because of our assumption of inexpensive natural gas, this point serves as our minimum retirement rate (i.e. 1.66% per year). The simulations in this work assume a retirement rate commensurate with a 50-year technical lifetime of a coal power plant (i.e. 2.00%), which serves as the mean the parameter distribution. The maximum retirement rate so is chosen to be 2.34%, which reflects about a 43-year lifetime. In both scenarios, we are interested in the impact on the standard distribution of main results: total CO_2 emissions.

Before introducing these distributions, we first determine the bounds of the total CO_2 emission result with the uncertainty described above. The first scenario tests the lowest gas price and highest retirement rate (i.e. $3.09 per MMBTU and 2.34% capacity retired annually), and the second scenario tests the highest gas price with the slowest retirement rate (i.e. $5.64 and 1.66%) to determine the extrema of the sensitivity analysis. These two tests bound the CO_2 results in the reasonable range where higher coal retirement rates accompany low gas prices and vice versa. The bounds are between 25.5% and 26.4% reductions from 2005 levels. The following paragraphs describe the sensitivity around with the distributions of uncertainty we chose.

We use the Systematic Sensitivity Analysis feature of the GEMPACK software to introduce this distribution of gas price and coal power retirement rates in separate simulations (Arndt, 1996; Arndt and Pearson, 1998). Separate simulations imply independence when, in reality, these are not (i.e. higher retirement rates would accompany low gas prices, and vice versa). Therefore, the results are more sensitive in these simulations than in the extrema analysis described above. The software uses a Gaussian Quadrature approach to determine a set of parameters and weights which permit computation of the mean and standard deviation of total CO_2 emissions, as well as other endogenous variables. All other descriptors and shocks detailed in the BAU remain unchanged. The table below shows the results:

Table E.1. Systematic sensitivity analysis of simulation model to gas price and coal power retirement rate.

	Input distribution						**Output (total CO_2)**				**Sensitivity**	
	Dist. Type	Min	Peak	Max	SD	CV	Mean	SD	CV	90% CI	SD Ratio	CV Ratio
Gas Price	Tri-angle	-56.6% ($3.09)	-38.7% ($4.36)	-20.7% ($5.64)	7.33% ($0.52)	0.189	-27.7%	1.45%	0.052	27.2% - 28.2%	0.197	0.275
Coal Retire Rate	Tri-angle	1.66%	2.00%	2.34%	0.136%	0.068	-26.0%	1.40%	0.054	24.3% - 27.6%	10.29	0.794

Note. SD is standard deviation and CV is the coefficient of variation.

From the coefficient of variation (CV) ratio shown in Table E.1 above we can see that the model is less sensitive to gas prices and more sensitive to coal power retirements. In a fully endogenous model, coal retirement rates would be a function of gas prices, as well as other factors, indicating that the simulation model could be more sensitive to the gas price changes. While, the model is well-suited to analyze the combination of gas price and coal retirement rate for the research question at hand, further work is necessary to calibrate the price responsiveness of coal power retirement rates to fuel prices in order to explore emission changes in response to other gas prices, such as the EIA gas price assumption.

In order to compare our results to the EIA Annual Energy Outlook 2016, we select a retirement rate that we believe may accompany the EIA assumed price of natural gas of $4.87, or a 31.5% decrease from 2007 prices. Because of the decline, we maintain our assumption of no new coal power plants; however, we adjust the retirement rate to match the technical retirement (i.e. 1.66% of capacity per year) rather than the expedited economic retirement rate (i.e. 2.00% per year) observed with the 45.8% gas price decline used in the article simulations. With EIA gas price projections for 2030 accompanied by an adjusted coal power retirement rate, the model projects a 25.6% reduction in total sector-wide emissions. This is lower than the reductions projected in the BAU simulations, but close to the EIA projections of a 23.6% reduction in emissions.

This sensitivity analysis demonstrates the sensitivity of the model to key drivers and assumptions. The model is robust to small changes in these drivers; however, more work is needed if larger assumptions, such as the "no new coal power capacity" assumption, is to be relaxed, as would be in the case of a return to "old normal" gas prices.

References

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