

Do Lower Electricity Storage Costs Reduce Greenhouse Gas Emissions?

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July 2017

Abstract

In the electricity sector, innovation in large-scale storage is anticipated to reduce costs and improve performance. The effect on greenhouse gas emissions of lower storage costs depends on the interactions between storage and the entire grid. The literature has disagreed on the role of storage in reducing emissions. In this paper we present a stylized model, which suggests that the effect of storage costs on emissions depends on the supply responsiveness of both fossil and renewable generators. Under common conditions in the United States, lower storage costs are more likely to reduce emissions when wind investment responds to equilibrium electricity prices and when solar investment does not. Simulations of a computational model of grid investment and operation confirm these intuitions. Moreover, because of its effect on coal and natural gas-fired supply responsiveness, introducing a carbon dioxide emissions price may increase the likelihood that lower storage costs reduce emissions.

Key Words: Bulk storage, batteries, innovation, research and development, wind power, solar power, renewables, greenhouse gas emissions, mathematical programming, optimization

JEL Classification Numbers: L94, Q4, Q5

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1. Introduction

In the absence of policy intervention, private decision makers do not consider the external costs of greenhouse gas emissions, such as using electricity generated by fossil fuel combustion. Standard economic theory suggests that setting an emissions price equal to social damages, via either an emissions tax or cap-and-trade, is the welfare-maximizing approach to addressing this market failure. However, policymakers seeking to reduce greenhouse gas emissions have demonstrated a preference for subsidizing low-emitting technologies rather than fully pricing emissions. A vast array of explicit and implicit subsidies for low-emitting technologies exists, such as renewables tax credits and requirements that renewables provide a specified fraction of electricity generation. Although some policymakers have adopted an emissions price, the price rarely if ever fully internalizes the costs of greenhouse gas emissions. For example, recent attempts to reduce US electricity sector emissions would have imposed an emissions price of approximately \$10 per ton of carbon dioxide (Energy Information Administration (EIA) 2014), which is likely to be substantially lower than the external cost of emissions (Greenstone et al. 2013; Nordhaus 2014).

Several recent articles argue that subsidizing low-emitting technologies is not economically efficient. Subsidizing the adoption of low or zero-emissions technologies reduces the private costs of adopting these technologies. However, Holland et al. (2009), Fell and Linn (2013), and others show that these policies can have ambiguous effects on emissions and social welfare. For example, subsidizing wind- and solar-powered electricity generators can reduce electricity prices, increasing consumption and generation from fossil fuel-fired generators. This effect can offset the emissions reductions from such policies, reducing efficiency compared with an emissions price.

Under the rationale of subsidizing low-emitting technologies, subsidies for research and development (R&D) and adoption of large-scale electricity storage are also becoming more widespread. For example, since 2009 the US Department of Energy has provided roughly \$200 million in funding for such storage research. Storage subsidies are commonly supported by the view—which many recent studies (e.g., de Sisternes et al. 2016) have largely confirmed—that electricity storage reduces the costs of achieving very high levels of renewables generation and limiting greenhouse gas emissions, as well as providing other benefits to the electricity system. Because electricity production from wind- and solar-powered generators is more difficult to control than production from conventional technologies, integrating large amounts of wind and solar increases the challenge of balancing electricity demand and supply. Storage can address this challenge by charging the storage device when electricity supply is abundant relative to

demand, and discharging when supply is scarce. According to this view, subsidizing storage R&D and adoption reduces the costs of integrating renewables and reduces emissions (or, alternatively, reduces the cost of meeting an emissions objective).

However, Carson and Novan (2013) and Graff Zivin et al. (2014) provide an alternative view of storage. They show that adding an incremental amount of storage can increase greenhouse gas emissions by causing a shift in generation from lower- to higher-emissions sources, such as from natural gas- to coal-fired generation. Thus, a central question for storage policies is whether anticipated reductions in the cost of storage will reduce emissions—that is, whether the widespread view of storage as facilitating emissions reductions is valid. The literature has provided conflicting views on this question.

We reconcile these opposing views of storage by taking an alternative approach, in which we consider potentially large amounts of storage and renewables capacity added to the existing grid, and analyze the effects of storage costs on emissions. Previous studies differ in the time horizon, either considering an incremental amount of storage added to the existing grid (e.g., Carson and Novan 2013) or redesigning the entire power system in the long run (e.g., de Sisternes et al. 2016). A short-run analysis is confined to the interaction between storage and existing generators, and cannot assess whether storage reduces the cost of integrating renewables. In contrast, we consider the medium run, a timeframe of 10 to 20 years, and include the interaction between storage and investment in new electricity generators. We focus on renewables investment because the literature has emphasized the relationship between storage and emissions in reducing emissions (de Sisternes et al. 2016). The medium run, rather than the long run, is the relevant timeframe for studying current policies that affect storage costs and near-term investment in generation and storage capacity.

Whereas most other studies analyze the effects of an exogenous increase in storage capacity (e.g., Walawalkar et al. 2007; Sioshansi et al. 2009; Nyamdash et al. 2010), we consider a context in which storage investment depends on storage costs and other market factors. This focus is motivated by several considerations. First, in practice, storage investment depends on decisions made by individual investors (in some cases with regulatory oversight) in response to market conditions, but most previous studies have treated storage as exogenous to the model. Second, the focus on storage costs is relevant to storage policies, which primarily reduce storage costs in the short run (via investment incentives) and the long run (via R&D subsidies). Third, partly but not entirely because of storage policy, technological innovation over the coming years is likely to reduce storage costs (Kintner-Meyer et al. 2010). In the context of declining costs, the

most relevant question for the future of storage is how the anticipated reduction in storage costs will affect emissions and other outcomes.¹

We argue that the effect of storage costs on emissions depends on the responsiveness of generation technologies to electricity prices. We focus on storage used for arbitrage purposes, charging when wholesale electricity prices are low and discharging when prices are high (wholesale prices are the prices received by electricity generators supplying electricity to retailers or utilities). We begin by using a simple, stylized model of a wholesale power market that generalizes Carson and Novan (2013) to include investments in wind and solar power generation. The model illustrates intuitively why the effect of storage costs on emissions depends on relative supply responsiveness—mathematically, the derivative of generation with respect to electricity price—of fossil fuel-fired and renewables generation plants. We confirm this intuition using a computational model calibrated to the Texas power system.

More specifically, we begin by noting that storage charging and discharging raises equilibrium prices during what would otherwise be low-price periods and reduces prices during what would otherwise be high-price periods; in the extreme case of free storage, equilibrium prices are equal across periods. Storage therefore has two effects on operation and investment of generators. The first is that storage raises generation from existing fossil-fired generators in low price periods and reduces generation from existing fossil-fired generators in high-price periods. As we show empirically for Texas, coal-fired generation is typically more price responsive than is natural gas-fired generation during low-price periods, whereas natural gas-fired generation is typically more price responsive than is coal-fired generation during high-price periods. Importantly, this is true for Texas even given the decline in natural gas prices that occurred after 2008. Therefore, reducing storage costs raises storage capacity and causes a shift from natural gas- to coal-fired generation. Because coal-fired generation is more emissions intensive than natural gas-fired generation, given estimated price responsiveness, a decrease in storage costs raises emissions; this is the effect that Carson and Novan (2013) identify.

The second effect is novel: it is the response of renewables investment to storage. For wind- and solar-powered generators, it is useful to focus on the responsiveness of investment with respect to the generation-weighted average electricity price. Renewables generation may be

¹ If storage raises emissions, subsidizing storage R&D could improve welfare by correcting market failures associated with early-stage technologies, such as learning spillovers and capital market failures (Fischer and Newell 2008; Acemoglu et al. 2012). However, this economic justification pertains to all early-stage technologies, and not specifically to storage, in which case R&D subsidies should be offered to technologies including but not limited to storage.

positively or negatively correlated with electricity price changes caused by storage, depending on the availability of the underlying resource and other factors. For example, in many regions wind generation peaks during the nighttime, when electricity demand and prices tend to be low. In that case, storage would increase nighttime electricity prices, and wind generation would be positively correlated with the electricity price changes caused by adding storage. This situation could apply to solar at high levels of solar penetration. When renewables generation—either wind or solar—is positively correlated with electricity price changes, lower storage costs raise the generation-weighted average electricity price and therefore renewables investment, displacing fossil fuel-fired generation and emissions. In this case, the more price responsive is renewables investment, the more likely that lower storage costs reduce emissions.

In contrast, when renewables generation is negatively correlated with electricity price changes caused by storage, reducing storage costs reduces the generation-weighted average electricity price, causing renewables investment to decrease. Lower renewables investment implies lower renewables generation, which raises fossil fuel-fired generation and emissions. Therefore, the more price responsive is renewables investment, the more a reduction in storage costs reduces renewables investment and raises fossil generation and emissions. This is often the case for solar, particularly at low levels of penetration. In short, the effect of storage costs on renewables investment depends on the correlation between generation from the renewables and storage-induced electricity price changes.

Thus, the stylized model suggests that the effect of storage costs on emissions depends on the price responsiveness of fossil fuel-fired and renewables generation. We confirm this intuition using a more detailed optimization model that endogenizes storage operation, dispatch of coal and natural gas-fired generators, and investment in storage, wind, and solar. The model accounts for the nondispatchability of renewables and includes supply curves for renewables and fossil fuel-fired generators. The model is calibrated to reproduce observed short-run substitution between fuels and current long-run investment projections. Applying the model to the Texas power system (i.e., the Electric Reliability Council of Texas, ERCOT), we first consider the case of zero renewables investment, which is comparable to Carson and Novan (2013). We find that lower storage costs increase storage investment and raise emissions precisely for the reasons identified in the stylized model: coal-fired generation is more price responsive during low-price periods, and natural gas-fired generation is more price responsive during high-price periods. This relative supply responsiveness is true even accounting for the fact that current forecasts of natural gas prices cause many natural gas-fired units to have lower generation costs than coal-fired units.

As in much of the United States, in ERCOT wind generation is positively correlated with storage-induced electricity price changes, and solar generation is negatively correlated. If we allow for wind and solar investment, lower storage costs raise emissions, as in the case without investment. However, changes in the price responsiveness of wind and solar investment have the predicted effects: a reduction in storage costs is more likely to reduce emissions the more price responsive is wind investment, and a reduction in storage costs is less likely to reduce emissions the more price responsive is solar investment. These results demonstrate the importance of price responsiveness in determining the effects of storage costs on emissions. In regions other than ERCOT, solar generation may be negatively correlated with storage-induced electricity price changes. In that case, lower storage costs would be more likely to reduce emissions the more price-responsive is solar investment—but even in that case lower storage costs would not necessarily reduce emissions.

An extension of our stylized model suggests that a carbon price has an ambiguous effect on the likelihood that lower storage costs reduce emissions. On the one hand, the carbon price causes fossil fuel-fired generation to be less price responsive relative to wind generation, which raises the likelihood that lower storage costs reduce emissions. On the other hand, the carbon price causes fossil fuel-fired generation to be less price responsive relative to solar generation, which reduces the likelihood that a reduction in storage costs reduces emissions. In the baseline model calibration, adding a carbon price makes it less likely that lower storage costs raise emissions.

Our paper contributes to the literature in several ways. First, we characterize an internally consistent set of supply conditions under which lower storage costs reduce carbon emissions. In contrast, Carson and Novan (2013) hold fixed renewables investment, and long-run studies do not characterize these supply conditions. Second, because wind investment responsiveness is central to the relationship between storage costs and emissions, we present the first attempt to estimate this responsiveness directly from observed investment decisions. By comparison, other studies rely on simulation-based cost estimates. Third, our computational model endogenizes investment in storage, wind, and solar capacity; previous studies have treated one or more of these as determined outside the model. This allows us to consider the question most relevant to storage policies: how a reduction in storage costs affects emissions, given the makeup of the existing grid.

2. Stylized Representation of the Effects of Storage Costs on Emissions

This section uses a stylized power sector model to illustrate the central channels by which storage costs affect emissions. The model is set up to approximate conditions on ERCOT, and we discuss generalizations of the model in the Conclusion. In the stylized two-period model, storage reduces price differences between the two periods and has ambiguous effects on emissions.

2.1 Equilibrium without Storage or Renewables

The model structure is similar to Carson and Novan (2013) and Fell and Linn (2013). There are two time periods, which are labeled off-peak and peak. The off-peak period has instantaneous exogenous electricity demand of D_o and the peak period has demand of D_p , with $D_p > D_o$ (demand and generation are in megawatt hours, MWh). We use the terms off-peak and peak heuristically to reflect periods in which storage is charged and discharged; the periods could reflect nighttime and daytime, or alternatively midday and late afternoon. In both periods there is an exogenous set of coal- and natural gas-fired generators, and the total capacity of coal-fired generators is \bar{Q}_c , with $\bar{Q}_c > D_o$. Thus, there is sufficient coal-fired generation capacity to meet off-peak demand. Generators are competitive price takers and the marginal costs (in dollars per MWh) are expressed as $m_c = \beta_c Q_c$, where β_c is a positive constant and Q_c is coal-fired generation. The marginal costs of natural gas-fired generators are expressed as $m_g = \alpha_g + \beta_g Q_g$, where α_g and β_g are positive constants.

Figure 1 illustrates the market supply curve and the equilibrium off-peak and peak electricity prices (in dollars per MWh) under assumption (A1) that $\alpha_g > \beta_c \bar{Q}_c$. The natural gas-fired portion of the market supply curve lies above the equilibrium off-peak price.² Equilibrium off-peak and peak prices are

$$P_o = \beta_c D_o \tag{1}$$

$$P_p = \alpha_g + \beta_g (D_p - \bar{Q}_c) \tag{2}$$

with $P_p > P_o$ following from assumption (A1).

² As we argue below, the main analytical results depend on price responsiveness of coal and natural gas, and not on the fact that coal is less expensive than natural gas in the stylized model. Therefore, the results are more general than might appear.

Emissions equal the sum of coal- and gas-fired emissions across the off-peak and peak time periods. The emissions rate of coal-fired generation is e_c , in tons of carbon dioxide (CO₂) per MWh, and the emissions rate of gas-fired generation is e_g , with $e_c > e_g$. Total emissions, in tons of CO₂, are

$$E = (D_o + \bar{Q}_c)e_c + (D_p - \bar{Q}_c)e_g. \quad (3)$$

Importantly, in the off-peak period coal-fired generators are operating at the margin, and a hypothetical increase in off-peak electricity demand would raise the off-peak electricity price and coal-fired generation by moving along the coal-fired generation supply curve in Figure 1. In contrast, an increase in peak electricity demand would raise the peak electricity price and natural gas-fired generation by moving along the natural gas-fired generation supply curve in Figure 1. Although this situation is not universal in electricity markets, it is fairly common and is relevant to the numerical modeling below (Linn et al. 2014).

2.2 *Equilibrium with Storage*

In the following subsections we add investments in storage, wind, and solar to the model. We maintain the two-period structure of the model, and conceive of the model as representing a long-run steady state that includes investments and generation. We introduce to the model a storage technology that has an amortized capital cost of K_b per unit of storage capacity (in MWh). The amount of storage investment is endogenous, and investing in Q_b units of storage costs $K_b Q_b$, allowing the owner to store Q_b units of electricity in the off-peak period and discharge Q_b units in the peak period (we abstract from storage losses for simplicity).

The difference between the peak and off-peak prices creates an arbitrage opportunity. The owner of the storage can charge the device in the off-peak period at a cost of P_o dollars per MWh, then discharge in the peak period and receive revenue of P_p dollars per MWh. Assuming that owners of the storage technology are competitive price takers, any equilibrium with positive storage investment must satisfy the arbitrage condition: $K_b + P_o = P_p$. When this condition holds, the cost of storing electricity in the off-peak period (inclusive of capital costs) exactly equals the revenue of discharging in the peak period.

Relative to the no-storage equilibrium, storage raises coal-fired generation by Q_b in the off-peak period and reduces gas-fired generation by Q_b in the peak period (Panel B of Figure 1). These generation changes raise the off-peak price and reduce the peak price. Because $e_c > e_g$, the generation changes increase total greenhouse gas emissions.

We solve for the equilibrium amount of storage capacity in terms of the exogenous parameters by combining the storage arbitrage condition with a market clearing condition (total generation across the two periods equals total supply), along with price equations analogous to (1) and (2). This yields

$$Q_b = \frac{1}{\beta_c + \beta_g} \{ [\alpha_g + \beta_g (D_p - \bar{Q}_c) - \beta_c D_o] - K_b \} \quad (4)$$

The term in square brackets in equation (4) is the difference between the peak and off-peak prices in the no-storage equilibrium. Thus, storage capacity increases with the difference between peak and off-peak prices in the no-storage equilibrium. Furthermore, the storage capacity decreases with storage capital costs, K_b .

Total emissions with storage equal emissions without storage, plus $(e_c - e_g)Q_b$. That is, adding storage to the model raises emissions because the storage raises off-peak coal-fired generation and reduces peak natural gas-fired generation.

Equation (4), combined with the fact that $e_c > e_g$, implies that a decrease in storage capital costs raises emissions. The more price responsive is coal and gas generation (i.e., the smaller is the sum $\beta_c + \beta_g$), the more a given reduction in storage costs raises storage capacity. In turn, a larger increase in storage capacity translates to a larger increase in off-peak coal-fired generation and a larger decrease in peak gas-fired generation, causing a larger increase in emissions.

2.3 *Equilibrium with Renewable Investment and No Storage*

We return to the initial case with no storage technology, and instead allow for investment in wind and solar generation capacity. There is a large set of potential locations for the wind and solar generators to be constructed. At each location it is possible to construct a single generator that produces one unit of electricity. Generation from wind and solar is nondispatchable, meaning that the owner of a generator cannot control when it produces electricity. To approximate typical real-world temporal variation in the availability of wind and solar generation (e.g., in the ERCOT region), we assume that the wind generation is available only in the off-peak period and solar generation is available only in the peak period. As with the off-peak and peak labels, the wind and solar technologies are heuristics; the terms wind and solar refer to renewables that generate electricity when storage is charged and discharged, respectively.

For both wind and solar generators, the marginal cost of producing electricity is zero, but there is a positive capital cost. Recall that the two-period model represents a long-run steady state, so that capital costs are amortized. Investors choose to construct generators at locations as long as the equilibrium electricity price exceeds the amortized capital costs. We assume that the distribution of capital costs across locations is such that wind and solar generator investment levels are proportional to the corresponding electricity prices: $Q_w = P_o / \delta_w$ and $Q_s = P_p / \delta_s$; we refer to these equations as the investment functions.

We focus on an equilibrium in which investors construct wind generators that produce electricity in the off-peak period, and they construct solar generators that produce electricity in the peak period. Therefore, the wind generators displace coal-fired generation and the solar generators displace gas-fired generation, relative to the initial equilibrium. Given the coal supply ($P_o = \beta_c D_o$) and wind investment function ($Q_w = P_o / \delta_w$), the equilibrium coal-fired generation in the off-peak period is

$$Q_c = \frac{\delta_w}{\beta_c + \delta_w} D_o. \quad (5)$$

Greater off-peak demand or less price responsive wind generation (higher δ_w) raises coal-fired generation (because of intermittency we use the term price responsiveness of wind generation interchangeably with the term price responsiveness of wind investment).

We assume that the parameter values are such that coal continues to operate at full capacity in the peak period, \bar{Q}_c . Therefore, the solar generation is

$$Q_s = \frac{\alpha_g}{\beta_g + \delta_s} + \frac{\beta_g}{\beta_g + \delta_s} (D_p - \bar{Q}_c). \quad (6)$$

Solar generation increases with the relative cost of natural gas to solar, and with peak period demand.

Combining the equilibrium solar generation with the fact that peak demand equals peak generation yields gas-fired generation in the peak period:

$$Q_g = \frac{\delta_s}{\beta_g + \delta_s} (D_p - \bar{Q}_c) - \frac{\alpha_g}{\beta_g + \delta_s}. \quad (7)$$

Gas-fired generation increases with peak demand net of coal-fired generation, and increases with the cost of solar relative to natural gas.

2.4 Equilibrium with Storage and Renewables

The final case includes endogenous investment in storage and wind. As in the previous equilibrium with storage, the storage capital costs determine the difference between the off-peak and peak prices: $K_b + P_o = P_p$. A reduction in storage capital costs therefore reduces the price difference, but in this case the increase in the off-peak price causes wind investment to increase, in addition to raising coal-fired generation. We show next that overall emissions can decrease if wind investment increases by a sufficient amount, which in turn depends on the responsiveness of wind relative to coal-fired generation.

We solve for the equilibrium coal and gas-fired generation using the no-arbitrage equation ($K_b + P_o = P_p$) and three equilibrium conditions. First, demand across the two periods equals total supply $Q_c + Q_w + \bar{Q}_c + Q_g = D_o + D_p$. Second, the marginal cost of coal-fired and wind generation equals the off-peak price, and $P_o = \beta_c Q_c = \delta_w Q_w$. Third, the marginal cost of gas-fired generation equals the peak period price: $P_p = \alpha_g + \beta_g Q_g$.

Combining the arbitrage and equilibrium equations allows us to solve for the equilibrium coal and gas-fired generation levels in terms of the exogenous parameters. Because emissions are expressed as $E = Q_c e_c + Q_g e_g$, we can solve for the derivative of emissions with respect to storage costs:

$$\frac{dE}{dK_b} \propto \beta_c e_g - \delta_w (e_c - e_g). \quad (8)$$

The less price responsive is coal-fired generation (higher β_c), or the more price responsive is the wind investment (lower δ_w), the more likely that a decrease in storage costs reduces emissions (i.e., the derivative is positive).

A similar result applies to solar, except that a decrease in storage costs is more likely to reduce emissions the less price responsive is solar investment. The intuition is that the reduction in storage costs raises storage investment and the quantity of storage, Q_b , reducing total generation during the peak period. Greater price responsiveness of solar investment implies a larger decrease in solar generation and an increase in fossil fuel's share of total generation.

To summarize, the stylized model yields three results:

- In the absence of renewables investment, a decrease in storage costs raises emissions by causing a shift from natural gas- to coal-fired generation.

- When renewables generation is positively correlated with electricity price changes caused by storage (i.e., wind in the stylized model), a decrease in storage costs is more likely to reduce emissions the *more* price responsive is renewables investment.
- When renewables generation is negatively correlated with electricity price changes caused by storage (i.e., solar in the stylized model), a decrease in storage costs is more likely to reduce emissions the *less* price responsive is renewables investment.

These results follow directly from the fact that storage affects coal- and gas-fired generation in different directions, as well as from the nondispatchability of renewables. In the specific cases considered here, a reduction in storage costs affects wind and solar in different directions, and the net effect on emissions depends on the price sensitivity of renewables generation relative to that of fossil fuel-fired generation. In the following sections, we use a more detailed model of investment and generator dispatch to confirm the intuition provided by the simple model.

3. Computational Model, Data, and Model Validation

3.1 Overview of the Computational Model

This section outlines the computational model that we use to confirm the intuition from the previous section (the appendix contains details of the model formulation). The stylized model contains only two time periods, reflecting off-peak and peak demand hours. The two time periods roughly capture the correlations among demand, wind generation, and solar generation, and the computational model includes a larger set of time periods to more accurately capture these correlations.

The model is calibrated to the ERCOT power system for several reasons. First, ERCOT is largely isolated from the remainder of the US power system, and many other studies (e.g., Carson and Novan 2013) have taken advantage of this feature, which simplifies the modeling. Second, the generation shares for coal and natural gas are roughly equal to the overall US average. Third, the correlations among demand, wind, and solar are fairly typical of much of the United States. On the other hand, ERCOT's share of wind in total generation is more than twice the US average, and the solar share is less than the US average. Section 6 discusses the implications of the simulation results for other regions.

For modeling convenience, we formulate the model as a cost minimization problem, which can be decentralized as a competitive equilibrium. The model consists of an initial

investment stage followed by a generation stage. The model contains six technologies that can supply electricity to meet demand: coal-fired generators, natural gas-fired generators, nuclear generators, solar generators, wind generators, and a storage unit.

The capacities of nuclear, coal, and natural gas-fired generation are exogenous. As explained below, the capacities of these technologies reflect current projections of capacity in the year 2030, given expected fuel prices and policies (the projections incorporate currently planned retirements and new construction). In the investment stage, the model determines whether to add capacity for the solar and wind generators, as well as for the storage unit. Investment costs of these technologies are calibrated to match current investment projections. We allow for endogenous wind and solar but not for other generation technologies to highlight the interactions among renewables and storage, which has been the focus of the storage literature. The endogeneity of solar and wind is consistent with market conditions, in that Texas does not have a binding Renewable Portfolio Standard (RPS).³ As we explain below, the storage scenarios we consider would likely have small effects on investment and retirements of coal, natural gas, and nuclear, supporting the exogeneity assumption..

The generation stage includes one year, which reflects demand and supply conditions forecasted for the year 2030. For computational reasons the model contains a subset of hours within the year; we choose the first week of each quarter of the year, for a total of 28 days (i.e., 672 hours). This set of hours captures the variation in demand and generation from wind and solar over the course of the year.

Hourly demand is exogenous. Hourly capacity factors of the wind, solar, and nuclear generators are also exogenous, and hourly generation from these technologies is equal to the capacity factor multiplied by the total capacity of the technology.

Generation from natural gas and coal is determined endogenously. Each generator produces an incremental amount of electricity. Any particular generator produces electricity and incurs marginal costs that depend on fuel and nonfuel costs. Each generator is a price taker and operates if the electricity price exceeds its marginal costs, and does not operate otherwise. Marginal costs vary across generators such that, for each technology, generators can be arranged in order of increasing marginal costs, yielding a smooth and differentiable supply function. A functional form is chosen and the parameters are calibrated to approximate observed fuel

³ Even in states that have a binding RPS, wind and solar investment are likely to be endogenous because states set their RPS in response to market and other policy conditions. For example, California has repeatedly increased the stringency of its RPS as existing targets are reached and investment costs decline.

consumption. To approximate real-world operating constraints, coal-fired generators cannot operate below a specified share of rated capacity.

The hourly electricity price equates supply and demand. The net electricity supply from the storage unit is determined endogenously, and the net hourly revenue accruing to the storage unit is equal to net supply (discharge less charge), multiplied by the equilibrium electricity price.

In short, the objective of the model is to minimize the capital and operating costs of meeting demand each hour of the year subject to initial conditions and supply constraints, and given capital and operating cost functions. Capital costs, operating costs, and revenues are annualized.

3.2 *Data, Parameter Estimation, and Calibration*

3.2.1 *Hourly Demand and Capacity Factors*

Hourly demand is constructed from ERCOT data on hourly electricity load for 2004, 2005, 2006, and 2008. For the first week of each quarter, we compute the average hourly total load across the four years. Between 2003 and 2010, hourly load in ERCOT increased by 0.71 percent per year. We assume that load grows at about 1 percent per year between 2015 and 2030, which is consistent with the EIA 2016 Annual Energy Outlook and ERCOT (2014).

For wind and solar, we define the investment cost function as the level of investment costs as a function of the investment level. Wind and solar operating costs are much lower than for other technologies, and the average cost per unit of generation depends primarily on the up-front capital costs and the average capacity factor (average hourly generation normalized by capacity). Computational models in the literature (e.g., Burtraw et al. 2015) rely on engineering-based estimates of capital costs and capacity factors. Typically, capital costs per unit of capacity do not vary across locations. Under these assumptions, total investment for wind or solar increases with the generation-weighted average electricity price because as the electricity price increases, wind and solar generators are constructed at locations with progressively lower capacity factors. We take an alternative approach and derive an empirically based investment cost function for wind, such that investment costs vary across locations. This subsection describes how we estimate the hourly capacity factors, and the next subsection describes how we estimate the investment cost function.

To construct hourly wind capacity factors, we use a set of simulated hourly wind generation that we obtained from ERCOT, which AWS Truewind assembled from meteorological data (Castillo and Linn 2011; Fell and Linn 2013). The data contain simulations

for 696 sites that were identified in a transmission planning study as among the most promising wind locations in the state. The simulations are based on wind and meteorological data, and there is heterogeneity in the production across wind sites. We compute the average capacity factor across all sites, and then use the capacity factors from the first week of each quarter.

Because the wind data cover the years 2004–2006, the demand and wind data are averaged over slightly different time periods. This likely does not have a substantial effect on the main results, however, because the periods coincide closely. Note that we assume that the correlations among demand, wind generation, and solar generation in 2030 are similar to those between 2004 and 2008.

The hourly solar capacity factors are computed based on simulation output from the National Renewable Energy Laboratory’s System Advisor Model (Fell and Linn 2013). Separate simulations are run for 17 cities in Texas, and hourly output is averaged across cities, again using the first week in each quarter.

Figure 2 illustrates the correlations among hourly demand, the wind capacity factor, and the solar capacity factor. Panel A shows a negative correlation between the hourly wind capacity factor and demand, which reflects variation both within days and across seasons of the year. Panel B indicates a positive correlation between the solar capacity factor and demand. The positive correlation arises because demand tends to be low at night, when the solar capacity factor is zero, and also because daytime demand tends to be positively correlated with the amount of sunlight.

Finally, we assume that nuclear generators have a capacity factor of 0.9 for all hours. This assumption is consistent with the estimated capacity factor from Davis and Wolfram (2012).

3.2.2 Existing Generation Stock

The initial conditions of the investment stage of the model include a set of existing nuclear, coal-fired, and natural gas-fired generators. We use the projected capacities of these technologies from the EIA 2016 Annual Energy Outlook, for the year 2030. The Clean Power Plan (CPP) sets electricity sector carbon emissions targets for each state, and was expected to cause a substantial shift from coal to natural gas-fired generation. However, because the CPP is likely to be made significantly less stringent than it was initially, we use projections of future generation capacity that do not include the CPP. The projections are from the EIA Annual Energy Outlook and they include the effects on generation capacity of the decline in natural gas prices since 2008, as well as other environmental regulations that have contributed to coal-fired

plant retirements. The projected generation stocks are: 4.9 gigawatts (GW) of nuclear, 16.7 GW of coal, and 58.9 GW of natural gas. We use projections from the EIA 2016 Annual Energy Outlook and ERCOT (2014) for wind and solar: 16.7 GW of wind, and 2.8 GW of solar.

3.2.3 Maringal Cost Curves for Coal- and Natural Gas–Fired Generation

We construct differentiable marginal cost curves for coal- and gas-fired generators based on operational data from the 2000s. For consistency with current capacity projections, the marginal cost curves include generators that are currently expected to come online, and exclude generators that are expected to retire.

In the model, marginal costs of natural gas– and coal-fired generators are the sum of fuel and nonfuel operating costs. We construct the marginal cost curves by estimating fuel and nonfuel portions separately, and then summing.

The cost of the fuel needed to generate one unit of electricity is equal to the price of fuel multiplied by the generator’s heat rate, which is the ratio of fuel input to net electricity generation (i.e., the reciprocal of fuel efficiency). We use net rather than gross electricity generation to account for electricity that is used to power the plant’s equipment. In the model, all generators face the same fuel prices, but fuel costs per unit of electricity generation vary across generators because of variation in heat rates. We characterize the variation in heat rates by estimating the relationship across generators between marginal fuel costs and cumulative generation capacity. We begin by computing the heat rate from EIA data for each coal- and natural gas–fired plant in ERCOT. We order coal-fired generators by increasing heat rate and compute the cumulative sum of rated capacity (also obtained from EIA data) for each generator, where the sum includes all generators with a heat rate no greater than that of the generator. For the capacity, we use the net summer capacity and assume a 10 percent outage rate. We exclude generators that are planned for retirement, and we include generators that are expected to come online within the next three years according to EIA. Thus, the sets of generators embodied in the supply curves include those expected to be in service in the near future.

We regress the cumulative sum of generation capacity on the unit’s heat rate. Multiplying the predicted heat rate functions by the corresponding projected Texas fuel prices for the year 2030 from EIA (2015) yields the fuel cost component of the marginal cost curves. The procedure is similar for natural gas–fired plants, except that we fit a cubic function in heat rate rather than a linear function. The functional form assumptions are chosen such that additional polynomials terms would not be statistically significant.

The model also includes heterogeneity in the nonfuel portion of marginal costs for natural gas-fired plants. If we were to assume that all generators have the same nonfuel portion of marginal costs, the resulting simulated electricity prices would exhibit less price variation than observed. This discrepancy may reflect underlying variation across generators in the nonfuel portion of marginal costs. Therefore, we calibrate nonfuel marginal costs to reproduce observed levels of electricity price variation. We assume that the nonfuel portion of marginal costs for natural gas-fired generators is a quadratic function of the level of generation, and we estimate the parameters such that the model yields a mean price similar to that observed in 2008. This calibration excludes hours in which observed prices are above \$500 per MWh, because such high prices likely reflect scarcity of available generation capacity, rather than marginal generation costs. We choose the quadratic function based on Linn and McCormack (2017).⁴ For coal-fired plants, we assume that nonfuel marginal costs are equal to variable operation and maintenance costs from EIA (2015). The marginal cost curves for gas and coal are the sums of the estimated fuel and nonfuel portions; see the appendix for further details.

Dynamic factors, such as constraints on rapidly varying generation levels across hours at coal- or natural gas-fired plants, could contribute to the observed price variation (Cullen 2015). For computational reasons we do not allow for such dynamics. The implications of omitting the dynamic operating constraints likely increase with the share of wind and solar power because these generation sources increase the temporal variation in the level of electricity that must be supplied by natural gas- or coal-fired generation. However, in the simulations, we consider modest increases in wind and solar generation from observed levels, mitigating this concern.

Figure 3 shows the marginal cost curves for natural gas- and coal-fired generation using two price levels—2008 and 2030. At both price levels the coal-fired curve is flatter than the natural gas-fired curve, suggesting that when coal-fired generation is not at full capacity, coal-fired generation is more responsive than gas-fired generation to changes in demand induced by storage or other factors; simulations of the year 2030 are consistent with this (see Section 4.1). The figure also indicates the degree to which the curves shift across the two periods. The year 2008 represents the maximum natural gas price in recent years, and prices in 2030 are projected to be somewhat higher than they have been recently but considerably lower than they were in 2008. The lower natural gas prices in 2030 cause a downward shift of the marginal cost curve for

⁴ Linn and McCormack (2017) estimate non-fuel costs from observed generator utilization, using a sample of natural gas-fired units located in the Eastern interconnection. Their analysis suggests that a quadratic function fits the observed variation well. Unfortunately, the sample of natural gas-fired units located in ERCOT is too small to reproduce their methodology for ERCOT.

natural gas. Coal prices in 2030 are projected to be similar to 2008 coal prices, and the coal marginal cost curves in the two years are similar to each other. Importantly for the results reported in the next section, in 2030 the coal marginal cost curve is flatter than the natural gas marginal cost curve, even accounting for the decline in natural gas prices that occurred after 2008.

3.2.4 Investment Cost Functions for Storage, Wind, and Solar

The total capital cost of the storage facility depends on its energy capacity (in kilowatt hours, kWh) and power rating (in kilowatts, kW). We assume that both capacity and power costs scale linearly with the capacity and power. Based on analysis described in the appendix, we assume that power is chosen to be proportional to capacity. Under these assumptions, the total capital cost is a linear function of the energy capacity. Kintner-Meyer et al. (2010) suggest that the total capital costs of typical battery storage facility are currently roughly \$400 per kWh. All costs reported in the following analysis include the costs of both energy capacity and power rating.

For wind and solar, we assume that capital costs per unit of capacity increase linearly with total investment. That is, the cost of the first unit of investment reflects the level of technology at a particular time; we select cost levels to reflect projected technology in 2030. Capital costs increase with the level of investment to reflect variation across locations in costs of construction, connecting to the grid, and so on. That is, similarly to other studies, we assume that wind generators are located at the sites with the lowest costs. Note that we assume that capital costs vary across locations, whereas many other studies assume that capacity factors differ across locations, but that capital costs do not vary. This difference is inconsequential in the current context, however, because either case would result in a positive relationship between equilibrium investment and the generation-weighted electricity price. We take this approach for modeling convenience.

As noted above, most computational models that include renewables rely on engineering-based estimates of costs. Instead of taking this approach, we make the first attempt to use observed investment decisions to estimate capital costs and variation in capital costs across locations. We perform this exercise for wind but not solar because of the limited investment in solar generators in ERCOT.

The intercept of the capital cost curve is the level of capital costs with zero investment beyond observed levels, and the slope is the change in capital costs for a one megawatt (MW) increase in investment. We calibrate the intercept and slope of the wind capital cost curve in

three steps. First, we simulate the model using 2010 data for fuel prices and demand. In the simulation, storage and solar investment are fixed at zero, but wind investment is endogenous. We calibrate the intercept of the wind capital cost function such that simulated wind investment equals the observed wind investment in 2010. Underlying this calibration is the argument that the intercept is sufficiently high to prevent additional investment beyond the observed level, and that capital costs will not change between 2010 and 2030. The assumption of constant costs is consistent with recent trends and with EIA projections. This calibration yields an estimated intercept of \$1,685 per kW of wind capacity, which is similar to the EIA estimate of \$1,560 from the 2016 Annual Energy Outlook (all values reported in this paper are in 2010 dollars).

An increase in the profitability of potential wind generators causes an increase in investment. The amount of investment depends on the slope of the capital cost curve; the steeper the curve, the less investment for a given profitability increase. Therefore, in the second step, we estimate the effects of market and policy factors on wind investment. Investment is a dynamic decision that depends on the expected profitability of a new wind generator. Because wind generators supply electricity to the grid, the value of their electricity depends on wholesale electricity prices. Fuel prices should positively affect wind investment because an increase in fuel prices raises wholesale electricity prices and the value of wind generation (Linn et al. 2014). Electricity demand should also have a positive effect on wind investment because an increase in demand raises electricity prices, all else equal. Moreover, in many years of the sample, the federal government has offered a production tax credit for new wind generators. The tax credit increases the revenue earned by a wind generator, stimulating investment, but the tax credit was unavailable in certain years of our sample, which may have affected investment in those and adjacent years. Note that Texas has a renewable portfolio standard that mandates a specific level of wind capacity, but in practice the standard has not been binding. Thus, investment may depend on fuel prices, electricity demand, and tax credits.

To estimate the effects of these factors on wind investment, we construct a panel data set of wind investment by year and ERCOT region for 1996 through 2015 (historically, ERCOT consisted of four regions, across which wholesale market prices could differ). We estimate a reduced-form model that links investment to proxies for future profitability assuming perfect foresight. The dependent variable is megawatts of wind investment, and the independent variables include the logs of natural gas and coal prices (from EIA), ERCOT-wide electricity

generation (a proxy for demand, from ERCOT), and a dummy variable equal to one in which the production tax credit was not available.⁵

Table 1 reports the results and indicates the expected relationships among the variables. In column 1, fuel prices have positive effects on investment, generation has a positive but statistically insignificant effect, and the absence of the production tax credit has a negative effect. Coal prices have a larger effect on investment than do natural gas prices, which is consistent with the negative correlation between wind generation and demand: during low-demand hours, coal-fired generators are more likely to determine wholesale prices than during high-demand hours (Castillo and Linn 2011; Carson and Novan 2013).

Column 1 uses current fuel prices, under the assumption that current fuel prices are proportional to expected future fuel prices. We relax this assumption in column 2 by replacing current fuel prices with forecasted prices that we construct based on EIA prices from 1980 through 1995 (i.e., prior to the estimation sample). The results are qualitatively similar, although the forecasted natural gas prices yield larger standard errors than the current prices, reflecting the limited variability in forecasted prices.

Column 1 includes demand-side influences on wind investment, and column 3 includes a supply-side factor: the log of the ratio of natural gas to wind capital costs, as estimated by EIA. Low wind costs should have a positive effect on investment, and the coefficient on this variable is expected to be positive. In practice, the estimated coefficient is negative but the standard error is very large, and we conclude that there is insufficient variation to identify this coefficient.

Column 4 reports results if we include a linear time trend, and column 5 uses annual observations aggregated across ERCOT. Across the five columns the coefficients usually have the expected signs, but the available variation prevents identification of some of the coefficients, particularly when the time trend is included. The time trend appears to absorb too much of the fuel price variation to identify those coefficients. We use column 1 as the basis for the calibration because the fuel price coefficients are precisely estimated; we note that we expect similar results if we use projected wind investment costs rather than estimated wind investment costs.

⁵ For most years of the sample, owners of wind generators received the production tax credit. Under current law, owners of future wind generators are eligible for an investment tax credit equal to 30 percent of the capital costs, which for most wind generators is more valuable than the production tax credit. Owners of wind generators cannot receive both tax credits, and the simulations for the year 2030 include the investment but not the production tax credit.

We perform this calibration by fixing initial wind capacity at 16 GW, which is the level of wind capacity in 2015. We use the model to simulate a baseline scenario using observed fuel prices, and a counterfactual scenario in which fuel prices are 10 percent higher than observed. We calibrate the slope parameter such that the change in investment is as close as possible to that predicted by the coefficients in column 1.

Because ERCOT has very few installed solar generators, we calibrate the solar capital cost curve without using market outcomes. We fix the vertical intercept at \$1,400 per kW, which is similar to the level assumed by ERCOT (2014) for future solar investment costs. We calibrate the slope of the cost function such that a simulation of 2030 demand and fuel cost conditions yields the 2.8 GW of solar that is currently projected.

3.3 *Model Validation*

Because the model is calibrated using data from the 2000s, we compare observed market outcomes with simulated outcomes for the three years with consistent data: 2004, 2008, and 2010. Table 2 reports the model inputs for each scenario in Panels A and B, and the simulated outcomes in the lower panels.

Comparing observed and simulated generation shares, the simulated nuclear and wind shares are typically slightly higher than the observed levels. In the case of wind, this could reflect the fact that the available wind capacity increased each year as new generators were constructed. The simulations use the amount of available capacity at the end of the year, which may cause the simulations to overstate the amount of wind capacity that was available on average during the year.

The simulated natural gas and coal generation shares are fairly close to the observed levels in 2004 and 2010 but differ more in 2008. Natural gas prices were lower in 2004 and 2010 than they were in 2008, suggesting that the model yields more accurate results for moderate natural gas prices. Reassuringly, the fuel prices used for the 2030 simulations in the next section are closer to the 2004 and 2010 levels than to the 2008 levels.

As noted above, the natural gas marginal cost curve was calibrated to roughly reproduce the observed mean electricity price in 2008. The simulated electricity prices have lower standard deviation than the actual prices in 2008, which appears to reflect the limitations of the model when natural gas prices are very high. In 2004, by contrast, the standard deviation of simulated prices is actually somewhat higher than the observed standard deviation (observed prices are not available in 2010).

Finally, Panel E reports the carbon dioxide emissions intensity across coal- and natural gas-fired generation, which is defined as the ratio of carbon dioxide emissions to generation. Consistent with the generation results reported in Panel C, the simulated carbon dioxide emissions intensity is similar to the actual intensity in 2004 and 2010 but differs more for 2008. Overall, we observe that the model reproduces observed outcomes to a reasonable extent, particularly when natural gas prices close to those modeled in the year 2030.

4. Effect of Storage Costs on Emissions

In this section we use the computational model to confirm the intuition from Section 2, that the effect of storage costs on emissions depends on the price responsiveness of natural gas, coal, and renewables.

4.1 Coal- and Gas-Fired Generation Only

First, we report simulations that characterize the effects of storage costs on emissions, assuming that wind and solar investments do not respond to storage costs. To provide some intuition for the results, given the emphasis in Section 2 on price responsiveness, we begin by using the computational model to characterize the price responsiveness of natural gas- and coal-fired generation. Figure 4 reports results from two scenarios based on 2030 fuel prices, using the baseline parameterization described in the previous section. In the first scenario, the hourly electricity demand is equal to the projected hourly demand in the year 2030. In the second scenario, demand in each hour is increased by 2 percent. In both scenarios, there is no investment in storage, wind, or solar. Natural gas- and coal-fired generation must increase to meet the higher level of demand.

The figure plots the change in hourly generation between the two demand scenarios for natural gas and coal on the vertical axis, and the hourly demand from the first scenario along the horizontal axis. Hourly demand increases from left to right in the figure, and the left-hand side of the figure includes nighttime and winter periods, whereas the right-hand side includes daytime and summer periods.

The figure indicates that when demand is below about 45,000 MWh, often coal responds more to a demand increase than does natural gas. Above 45,000 MWh, coal-fired generators are producing at their maximum capacity, and natural gas meets the entire demand increase. These patterns are consistent with the fact that the coal marginal cost curve is flatter than the natural gas marginal cost curve (see Figure 3). Figure 4 implies that adding storage, which tends to

increase generation in low-demand periods and decrease generation in high-demand periods, will cause an increase in generation from coal and (to a lesser extent) natural gas during low-demand periods, and a decrease in natural gas-fired generation during high demand periods. Therefore, reducing storage costs is likely to increase carbon dioxide emissions in the case when there is no wind and solar investment.

Building on this intuition, we report a series of simulations that characterize the effects of storage costs on emissions. We begin with our baseline model calibration and 2030 hourly demand and fuel prices. With these inputs, the model yields zero storage investment for storage costs above about \$280 per kWh. This cost is about two-thirds of recent cost estimates for storage (Kintner-Meyer et al. 2010) and is roughly comparable to the results in de Sisternes et al. (2016). Starting from this level of storage costs, we simulate the model at sequentially lower storage costs, considering up to a 50 percent reduction in storage costs.

Figure 5 shows the main results, illustrating storage costs on the horizontal axis and the percentage change in various outcomes relative to a case with zero storage investment on the vertical axis. For reference, Appendix Figure 1 shows the level of storage investment for this scenario and the other scenarios reported in later subsections. Table 3 reports the levels of the outcomes for the case of zero storage investment, when storage costs are \$280 per kWh.

Figure 5 indicates that coal-fired generation increases as storage costs fall. Natural gas-fired generation follows the opposite pattern, falling as storage costs fall. Overall, carbon dioxide emissions rise as storage costs fall, extending the conclusions of Carson and Novan (2013) to nonmarginal levels of storage investment. Thus, their conclusions are robust to modeling the projected makeup of the ERCOT system in the year 2030, which includes a substantial shift from coal to gas-fired generation relative to historical levels.

Lower storage costs reduce the average and standard deviation of electricity prices. The effect on average prices arises from the convexity of the natural gas-fired marginal cost curve (see Figure 3). Adding storage raises prices during low-demand prices but reduces prices during high-demand periods. Therefore, the more storage is added to the system, the more prices converge between low- and high-demand periods, reducing price variation.

To illustrate the effects of storage on hourly generation by fuel type, Figure 6 compares two scenarios: storage costs of \$280 per kWh (Panel A) and \$140 per kWh (Panel B). To construct the figure, we select the first four simulation days and plot hourly generation by fuel type. Panel A shows that with zero storage, wind generation tends to be highest during the low-demand hours, and that natural gas and coal vary production so that total generation equals total

demand. The variation in coal generation reflects the fact that given projected fuel prices, coal has much lower capacity factor than it has had historically, when coal typically operated closer to full capacity at all hours.

Comparing the two storage cost cases, reducing the cost of storage causes more coal- and natural gas-fired generation in low-demand hours, with a larger effect on coal-fired generation than on gas-fired generation. Storage reduces both coal- and natural gas-fired generation in high-demand hours. These results are consistent with the overall findings in Figure 5, that reducing storage costs causes a shift from natural gas- to coal-fired generation, raising emissions.

4.2 Adding Renewables Investment

To provide intuition for the interaction between storage and renewables, Figure 7 reports results from a set of demand simulations similar to those in Figure 4, except that wind capacity can increase in response to the demand increase. An increase in wind capacity causes hourly wind generation to increase in accordance with the hourly capacity factor. The figure shows that wind generation increases more during low-demand periods than during high-demand periods, which reflects the negative correlation between wind's capacity factor and demand. The increases in the low-demand periods are smaller than for coal and natural gas but are nonetheless substantial. Comparing Figures 4 and 7 indicates that coal- and natural gas-fired generation increase by less when wind capacity is endogenously determined, demonstrating the importance of accounting for renewables investment when assessing the effect of storage costs on emissions.

Figure 8 illustrates the effects of storage costs on generation, electricity prices, and emissions, allowing wind and solar investment to respond to storage costs. Each panel reports a single outcome, with the vertical axis plotting the percentage relative to zero storage investment (i.e., investment costs of \$280 per kWh). The solid lines indicate the scenarios with zero wind and solar investment for reference, and the dashed lines indicate the scenarios with endogenously determined wind and solar investment.

Panels A and B show that reducing storage costs lowers the natural gas-fired generation share and increases the coal share. On the one hand, the wind generation share increases slightly as storage costs decrease. The additional wind generation displaces mostly coal and to a lesser extent natural gas, which is consistent with the results shown in Figure 7. The displacement of coal and natural gas-fired generation by wind generation causes emissions to decrease. On the other hand, Panel D shows that lower storage costs reduce the solar generation share, which raises emissions. On balance, reducing storage costs causes a net increase in emissions. The

increase is slightly less than the increase that occurs when wind and solar investment are zero—in other words, when wind and solar investment are endogenous, declining storage costs are less likely to increase emissions than when wind and solar investment are zero.

Figure 9 plots the hourly generation by fuel type for the same two storage cost scenarios as shown in Figure 6, except allowing for positive wind and solar investment in the low storage cost case. The figure indicates a small amount of wind generation from new investment, reflecting the modest effect of wind investment on generation levels of coal and natural gas. Thus, using the baseline model calibration, we show that allowing for endogenous wind and solar investment does not overturn the finding that lower storage costs raise emissions, but it does mitigate the increase in emissions.

4.3 High Wind or Solar Price Responsiveness

In Section 2 the model suggested that the price responsiveness of wind investment affects the relationship between storage costs and emissions. In particular, a reduction in storage costs is more likely to reduce emissions the more price responsive is wind investment. We illustrate this effect by flattening the wind investment cost curve, which reflects potential innovation in wind technology that reduces the variation in capital costs across wind locations. Specifically, for illustrative purposes we assume that the wind investment cost curve is half as steep as in the baseline parameterization.

Figure 8 shows that increasing the price responsiveness of wind investment increases the wind generation share (Panel C), reducing both natural gas– and coal-fired generation (Panels A and B) relative to the baseline wind investment assumptions from Section 4.2. The reduction in fossil fuel-fired generation is sufficiently large to change the relationship between storage costs and emissions, as Panel G shows. These simulations indicate that if wind investment is sufficiently price responsive, a reduction in storage costs reduces rather than raises emissions.

Turning to solar price responsiveness, because solar generation is negatively correlated with storage-induced electricity price changes, we expect that an increase in solar price responsiveness reduces the likelihood that a reduction in storage costs lowers emissions. To illustrate this effect, we reduce the slope of the solar investment cost curve, which causes an increase in the amount of solar investment that occurs when storage investment costs are \$280 per kWh (i.e., when storage investment is zero; see Table 3). Starting from that equilibrium, Figure 8 shows that reducing storage costs from \$280 to \$140 per kWh reduces the solar generation share (Panel D) and increases the natural gas-fired generation share (Panel A). These

generation changes translate to a slight increase in emissions relative to baseline solar costs (Panel G). Thus, the simulation results are consistent with the intuition provided by the model in Section 2.

5. Interaction between Storage Costs and a Carbon Price

We extend the model in Section 2 to show that a carbon price has ambiguous effects on the relationship between storage costs and carbon dioxide emissions. Without storage, adding a carbon price causes a reduction in emissions because of a shift from coal- to gas-fired generation, and increases in wind and solar investment.

With storage, adding a carbon price affects emissions in accordance with the price responsiveness of electricity generation. We first show that a carbon price reduces the price responsiveness of coal- and natural gas-fired generation. To illustrate this effect, we construct a figure similar to Figure 4, except introducing a carbon price equal to \$30 per ton of carbon dioxide (the carbon price is implemented as a fuel tax). Figure 10 plots the effect of a 2 percent demand increase on coal and natural gas-fired generation. The figure, which includes the results from Figure 4 for reference, indicates a decrease in responsiveness for both coal- and gas-fired generation when demand is below 45,000 MWh. When demand is above 45,000 MWh, the carbon price does not affect the responsiveness, and the corresponding dots in the figure lie on top of one another.

Because of this effect, reducing storage costs has two opposing effects on renewables investment and emissions. On the one hand, adding a carbon price causes the coal-fired generation to become less price responsive. This causes wind investment to increase more given a storage cost reduction than in the absence of the carbon price. Consequently, a reduction in storage costs causes more wind investment and lower carbon emissions, compared with a scenario without a carbon price.

On the other hand, adding a carbon price also reduces the price responsiveness of natural gas-fired generation. Because the carbon price raises the price responsiveness of solar relative to natural gas, solar investment is more sensitive to the reduction in daytime electricity prices caused by a reduction in storage costs. As a result, a reduction in storage costs raises carbon emissions by more than in the absence of a carbon price.

Figure 11 illustrates the implications for total carbon dioxide emissions of the lower price responsiveness for both coal- and natural gas-fired generation. Introducing a price of \$30 per ton of carbon dioxide affects the relationships among storage costs, generation, prices, and

emissions. With a carbon price, reducing storage costs lowers emissions. However, because a carbon price has ambiguous effects on the relationship between storage costs and emissions, in some realistic model parameterizations that we have considered, a carbon price has the opposite effect.

6. Conclusions

The literature has disagreed on the greenhouse gas benefits of storage investment and innovation. In the short run, without power plant investment, lower storage costs may raise emissions because of a shift from natural gas– to coal-fired generation. In the long run, lower storage costs may reduce the cost of integrating renewables.

We focus on the medium run, or roughly 10–20 years, which is relevant for evaluating existing storage policies. Taking the makeup of the existing grid as exogenous, we assess the effects of reducing storage costs on emissions, accounting for investment and generation changes. In a stylized model, the effect depends on the price responsiveness of renewables and fossil fuel-fired generation. For renewables whose generation is positively correlated with electricity price changes caused by storage, the more price responsive is renewables investment, the *more* likely that a reduction in storage costs reduces emissions. Wind generation is often positively correlated with storage-induced electricity price changes, and higher wind responsiveness increases the likelihood that lower storage costs reduce emissions. In contrast, for renewables whose generation is negatively correlated with electricity price changes caused by storage—which is often true for solar—the more price responsive is renewables investment, the *less* likely that a reduction in storage costs reduces emissions. The contrasting effects arise because storage raises generation-weighted average prices in the first case but reduces generation-weighted average prices in the second case.

We use a computational model that relaxes many of the assumptions in the stylized model, and that is calibrated to approximate observed fuel consumption and current investment projections. Wind generation is positively correlated with electricity price changes caused by storage, and solar generation is negatively correlated. Therefore, the stylized model suggests that greater price responsiveness of wind investment increases the likelihood that lower storage costs reduce emissions, whereas greater price responsiveness of solar investment reduces the likelihood that lower storage costs reduce emissions.

The wind and solar results rest on the fact that in ERCOT solar generation is negatively correlated with storage-induced price changes. This may not be the case at particularly high

levels of solar generation, such as in California. If solar generation is positively correlated with price changes, an increase in price responsiveness for solar increases the likelihood that lower storage costs reduce emissions—just as for wind in ERCOT.

An extension of the stylized model shows that a carbon price has an ambiguous effect on the relationship between storage costs and emissions. Simulations of the computational model indicate that with a carbon price, a decrease in storage costs typically reduces emissions.

These results have several policy implications. First, policies incentivizing storage investment and R&D subsidies that reduce storage costs have ambiguous effects on emissions in the medium run. The policies could be justified by market failures for new technology, but our results do not provide strong evidence for supporting storage on the basis of medium-term carbon emissions reductions in the US. Second, introducing a carbon price does not necessarily imply that lower storage costs reduce emissions. Third, the effect of storage costs on renewables investment depends on the correlation between renewables generation and storage-induced electricity price changes. Fourth, in the baseline calibration, storage investment is positive when storage costs approximately two thirds of what it did in 2010. This suggests that further storage innovation will be needed for storage to be economically viable for arbitrage purposes. The level of storage costs needed to yield positive investment is sensitive to assumptions, however.

We note that the conclusions are based on scenarios that account for the effects on the electricity system of recent environmental regulations and declines in natural gas prices, which have contributed to the shift from coal to gas-fired generation. As discussed in Section 3, we treat natural gas and coal generation capacities as exogenous to focus on the relationship between storage and renewables. In practice, the reduction in storage costs that we consider reduces revenues for natural gas and coal by about 5 percent. This reduction is much smaller than the changes in coal-fired plant profits that occurred in the late 2000s and early 2010s following the decline in natural gas prices (Linn and McCormack 2017). This suggests that storage would have little effect on retirements of natural gas or coal, implying that the assumed exogeneity of coal and natural gas capacity has little effect on the results. Note that retirement of coal capacity would cause the coal supply curve to become steeper, increasing the likelihood that lower storage costs reduce emissions; natural gas-fired retirements would have analogous implications.

We suggest several directions for future research. First, the relationship between storage costs and emissions depends on the price responsiveness of generation technologies. Whereas available data make it possible to estimate this price responsiveness for coal- and natural gas-fired generation, there is very little research on the price responsiveness of investment for any

technology. We report results from a straightforward approach to estimating the price responsiveness of wind investment, which is sufficient for the paper's purpose of demonstrating the importance of price responsiveness in determining the relationship between storage costs and emissions. Future work could refine this estimation and consider other technologies besides wind.

Second, we have focused on the relationship between storage costs and carbon dioxide emissions. Because carbon dioxide is a globally mixed pollutant, the social damages of emissions do not vary over time or by location. Natural gas- and coal-fired generation emit other pollutants, such as nitrogen oxides, whose external costs vary over time and by location. Future work could characterize the societal benefits and costs of storage, accounting for pollutants other than carbon dioxide.

Third, we focus on the ERCOT power system for reasons described above. Future work should consider other regions, which have different levels of renewables and correlations between demand and renewables generation, compared to ERCOT.

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Appendix. The Electricity Generation and Storage Model

In this appendix, we discuss the mathematical programming model to investigate the interplay of fossil fuel electricity generation, renewable electricity generation, energy storage, carbon price, and greenhouse gas emissions. This model allows simultaneous consideration of dispatch of electricity and investment of new generation and storage capacities.

Appendix Figure 2 provides a schematic representation of the modeling domain. It includes a power system and pollution externalities. For simplicity, the power system is aggregated such that the electricity generators produce one unit of electricity and marginal costs are differentiable functions of generation. The generation technologies are natural gas, coal, nuclear, wind, solar, and storage (which includes the power conversion system). The energy storage facility can be charged using electricity supplied by any generator. For pollution, we focus on carbon dioxide pollution produced by natural gas– and coal-fired generation.

We formulate the model as a cost minimization problem, which solves the competitive equilibrium. At the end of the Appendix we discuss the competitive decentralization. The model consists of an investment stage followed by a generation stage. The objective is to minimize the cost of investment and generation subject to the constraint that hourly generation equals hourly demand, and subject to the initial conditions of the investment stage. The initial conditions of the investment stage include positive levels of generation capacity for natural gas, coal, nuclear, wind, and solar. During the investment stage, wind, solar, and storage capacity can be added according to the cost functions described below.

For computational reasons, the generation portion of the model consists of the first week of January, April, July, and October, to represent typical electricity demand and renewables generation levels of each season. The model simulates operations for 672 hours, annualizing all generation and investment costs. During the generation stage, we consider two types of electricity demand, including electricity consumption by consumers and electricity needed to recharging energy storage. For simplicity, we ignore losses in the power grid and energy storage systems.

The model considers hourly dispatch. In each hour, total generation equals total demand. Hourly generation for nuclear, wind, and solar is determined by the assumed capacity factors. Natural gas– and coal-fired generation have the marginal cost curves described below. Hourly carbon dioxide emissions are estimated using emissions factors for coal and natural gas.

The model is formulated as a nonlinear mathematical programming model and is solved using CONOPT nonlinear solver in GAMS (GAMS 2013).

The Model

Nomenclature

	$i \in \{\text{coal, NG, nuclear, wind_exist, solar_exist, wind_inv, solar_inv, storage}\}$
i	EGU index,
j	Pollutant index, $j \in \{\text{CO}_2\}$
t	Time index
D_t	Electricity demand at time t , known
GC_i	Electricity generation of EGU, i , $i \in \{\text{coal, NG, nuclear, wind_exist, solar_exist}\}$, known
MGF_i	Minimum generation factor for EGU i , $i \in \{\text{coal}\}$, known
CF_{it}	Capacity factor of renewable power generation at time t , $i \in \{\text{wind_exist, solar_exist, wind_inv, solar_inv, nuclear}\}$, known
$amor$	Amortization ratio, known
α_1, α_2	Natural gas marginal cost curve parameters, calibrated and known
a_i, b_i	Capital cost function parameters for EGU i , $i \in \{\text{storage, wind_inv, solar_inv}\}$, calibrated and known
P_c	Price of coal, known
P_g	Price of natural gas, known
EF_{ij}	Emission factor for pollutant j from source i , known
G_{it}	Electricity generation from EGU i , at time t , unknown
R_t	Storage recharge at the end of the time period t , unknown
S_t	Level of electricity storage at the end of the time period t , unknown
Q_i	Design capacity of i , $i \in \{\text{storage, wind_inv, solar_inv}\}$, unknown
CAP_i	Amortized capital cost for EGU i , $i \in \{\text{storage, wind_inv, solar_inv}\}$, unknown
MC_{coal_t}	Marginal generation cost for coal, unknown
MC_{ng_t}	Marginal generation cost for natural gas, unknown
TC_{coal_t}	Generation cost for coal at time t , unknown

$TCng_t$	Generation cost for natural gas at time t , unknown
P_t	Hourly electricity price, unknown
E_{ijt}	Net emission for pollutant j from source i at time t , unknown

Constraints

Electricity Generation from Fossil Fuels

Electricity generation from fossil fuel energy sources, coal and NG, at any time, t , are constrained by their generation capacities. That is,

$$G_{it} \leq GC_i \quad i \in \{\text{coal}, \text{NG}\}, t \quad (1)$$

Electricity Generation from Renewables

For wind and solar (both existing and new investment), the electricity generation for any specific time, t , is set equal to the capacity multiplied by the hourly capacity factor. Capacity factors are estimated as described in Section 3:

$$G_{i,t} = GC_i \times CF_{i,t} \quad i \in \{\text{wind_exist}, \text{solar_exist}, \text{nuclear}\}, \forall t \quad (2)$$

$$G_{i,t} = Q_i \times CF_{i,t} \quad i \in \{\text{wind_inv}, \text{solar_inv}\}, \forall t \quad (3)$$

Electricity Generation from Energy Storage

Electricity generation from energy storage is constrained by the energy storage capacity:

$$G_{i,t} \leq Q_i \quad i \in \{\text{storage}\}, \forall t \quad (4)$$

Minimum Generation Requirements

Coal and nuclear generators have minimum generation requirements. For coal, we assume a minimum of 0.2 percent of capacity. Nuclear has a minimum generation requirement of 0.9, and we assume that the costs of varying nuclear generation across hours is sufficiently high that nuclear operates at this required level for each hour.

$$G_{it} \geq GC_i \times MGF_i \quad i \in \{\text{coal}\}, \forall t \quad (5)$$

Balancing of Electricity Demand and Supply

For any hour, t , the total electricity generation across all sources (including storage) equals the sum of consumers' demand and charging from storage.

$$\sum_i G_{it} = D_t + R_t \quad i \in \{\text{coal, NG, nuclear, wind_exist, solar_exist, wind_inv, solar_inv, storage}\}, \forall t \quad (6)$$

Energy Balance for Bulk Storage

The level of electricity storage at the end of hour t is equal to the level at the end of previous time period, $t-1$, plus recharge, minus electricity discharge from the storage during hour t .

$$S_t = S_{t-1} + R_t - G_{i,t} \quad i \in \{\text{storage}\}, \forall t \quad (7)$$

Bulk Storage and Bulk Storage Design Capacity

At any hour, t , the level of storage cannot exceed the storage design capacity.

$$S_t \leq Q_i \quad i \in \{\text{storage}\}, \forall t \quad (8)$$

Cost Functions

Capital Costs for Energy Storage, Wind Generation, and Solar Generation

The model includes investment in energy storage (including the power conversion system), wind, and solar. We annualize investment costs using a 10 percent interest rate and 20-year lifetime (*amor*).

For the power conversion system, we estimate the relationship between maximum electricity discharge and energy storage capacity using a linear function. We use unit capital cost for power conversion systems (Kintner-Meyer et al. 2010). New wind and solar generators receive a 30 percent investment tax credit, *itc*.

The following equations provide the annualized capital cost for the power conversion system, energy storage, and new wind and new solar investments. We estimate the relationship between maximum discharge and storage capacity by simulating the model at various levels of storage capacity and observing maximum discharge in each simulation. The total storage investment cost is the sum of the cost of the power conversion system and the energy storage.

$$CAP_{pcs} = pcs \times power_storage \times Q_i \times amor \quad i \in \{\text{storage}\} \quad (9)$$

$$CAP_i = a_i \times Q_i \times amor \quad i \in \{storage\} \quad (10)$$

$$CAP_i = (1 - itc) \times (a_i + b_i \times Q_i) \times Q_i \times amor \quad i \in \{wind_inv, solar_inv\} \quad (11)$$

Generation Costs for Fossil Fuel Generators

As discussed in Section 3, the functional forms for the marginal cost curves for natural gas and coal are based on the observed variation in heat rates across existing generators. Total costs for each technology are the integral of marginal costs.

$$MC_{coal,t} = 20 + 9.731502 \times P_c + 0.0001068 \times P_c \times G_{coal,t} \quad \forall t \quad (12)$$

$$\begin{aligned} MC_{ng,t} = & \alpha_1 + \alpha_2 \times G_{ng,t}^2 + 4.331101 \times P_g + 0.0003511 \times P_g \times G_{ng,t} \\ & - (1.09372e - 8) \times P_g \times G_{ng,t}^2 + (1.578355e - 13) \times P_g \times G_{ng,t}^3 \end{aligned} \quad \forall t \quad (13)$$

$$TC_{coal,t} = 20 \times G_{coal,t} + 9.731502 \times P_c \times G_{coal,t} + (1/2) \times 0.0001068 \times P_c \times G_{coal,t}^2 \quad \forall t \quad (14)$$

$$\begin{aligned} TC_{ng,t} = & \alpha_1 \times G_{ng,t} + (1/3) \times \alpha_2 \times G_{ng,t}^3 + 4.331101 \times P_g \times G_{ng,t} \\ & + (1/2) \times 0.0003511 \times P_g \times G_{ng,t}^2 \\ & - (1/3) \times (1.09372e - 8) \times P_g \times G_{ng,t}^3 \\ & + (1/4) \times (1.578355e - 13) \times P_g \times G_{ng,t}^4 \end{aligned} \quad \forall t \quad (15)$$

Electricity Price

As noted in the main text, we formulate the model as a constrained cost minimization. The solution to the problem could be decentralized by assuming that all generator and electricity storage owners are price takers and operate as long as price exceeds marginal costs. In equilibrium, when coal-fired generation lies between its minimum generation level and total capacity, the electricity price equals the marginal costs of both natural gas and coal. When either coal generation constraint binds, the marginal cost of natural gas differs from that of coal. In all hours, because the natural gas level of generation is never constrained, the electricity price equals the marginal cost of natural gas.

$$p_t = MC_{ng,t} \quad \forall t \quad (16)$$

Carbon Dioxide Emissions

Emissions of coal and natural gas account for variation across generators in heat rates and for variation in carbon content across fuels.

$$E_{coal,co_2,t} = EF_{coal,co_2} \times (9.731502 \times G_{coal,t} + (1/2) \times 0.0001068 \times G_{coal,t}^2) \quad \forall t \quad (17)$$

$$\begin{aligned} E_{ng,co_2,t} = & EF_{ng,co_2} \times (4.331101 \times G_{ng,t} + (1/2) \times 0.0003511 \times G_{ng,t}^2 \\ & - (1/3) \times (1.09372e-08) \times G_{ng,t}^3 \\ & + (1/4) \times (1.578355e-13) \times G_{ng,t}^4 \end{aligned} \quad \forall t \quad (18)$$

Objective Function

The objective function is the annual cost, which includes annual operating costs for fossil fuel generators and annualized capital costs for power control system, energy storage, new wind and new solar investments. The number 13 is a scaling factor because we consider four representative weeks for fossil fuel generator operations in the model.

$$\begin{aligned} & \sum_t (TC_{coal,t} + TC_{ng,t}) \times 13 \\ & + (CAP_{pcs} + CAP_{storage} + CAP_{wind_inv} + CAP_{solar_inv}) \end{aligned} \quad (19)$$

Expression (19) is minimized subject to conditions (1) through (8), and with total costs and capital costs given by (9) through (11), (14), and (15). The decision variables are capacities of wind, solar, and storage, and hourly generation of each technology and of storage.

Table A1. Model Inputs

<i>Parameter</i>	<i>Unit</i>	<i>Value</i>
a_{wind_inv}	\$/MW	1,685,000
a_{solar_inv}	\$/MW	1,400,000
b_{wind_inv}		141.8
b_{solar_inv}		149.0
α_1		-22
α_2		1.2e-07
$power_storage$	MW/MWh	0.0926
$power_control_system$	\$/MW	75,000
P_c	\$/mmBtu	2.589
P_g	\$/mmBtu	6.007
$amor$	%	12
itc	%	30
MGF_{coal}	%	20
$MGF_{nuclear}$	%	90
$EF_{coal,CO2}$		0.11
$EF_{ng,CO2}$		0.056
GC_{coal}	MW	16,700
GC_{ng}	MW	58,900
$GC_{nuclear}$	MW	4,927
GC_{wind_exist}	MW	16,700
GC_{solar_exist}	MW	2,800

Figure 1. Effect of storage on market equilibrium

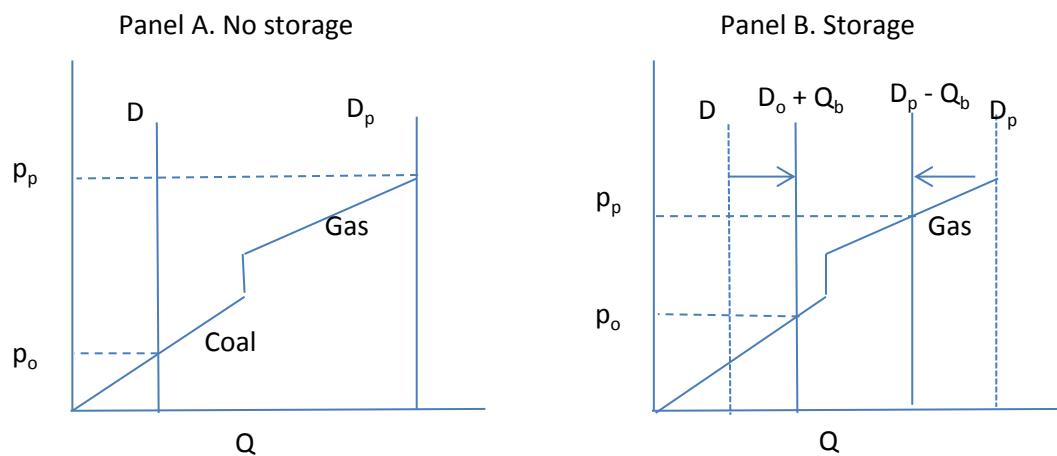


Figure 2. Correlations among demand, wind capacity factor, and solar capacity factor

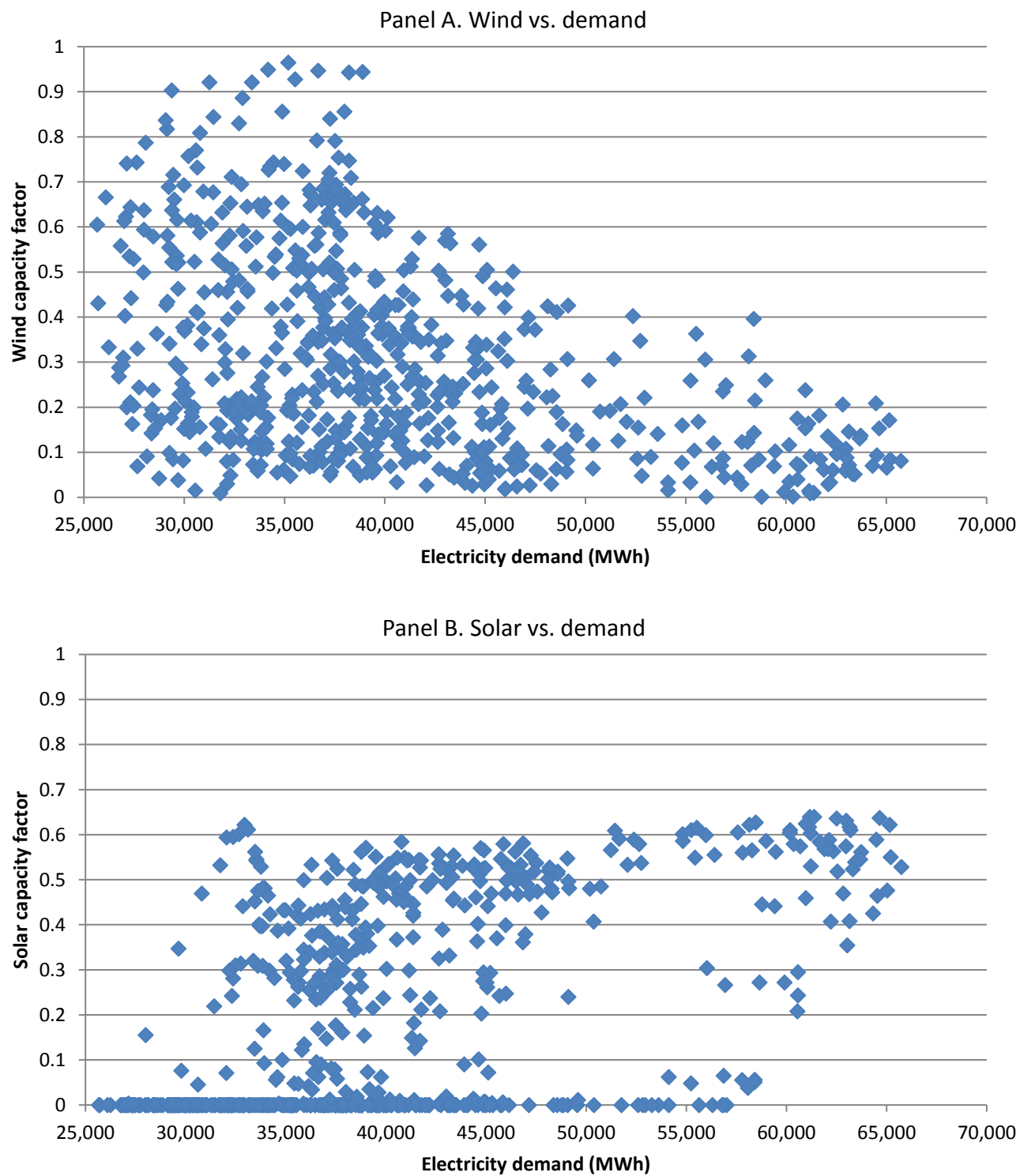
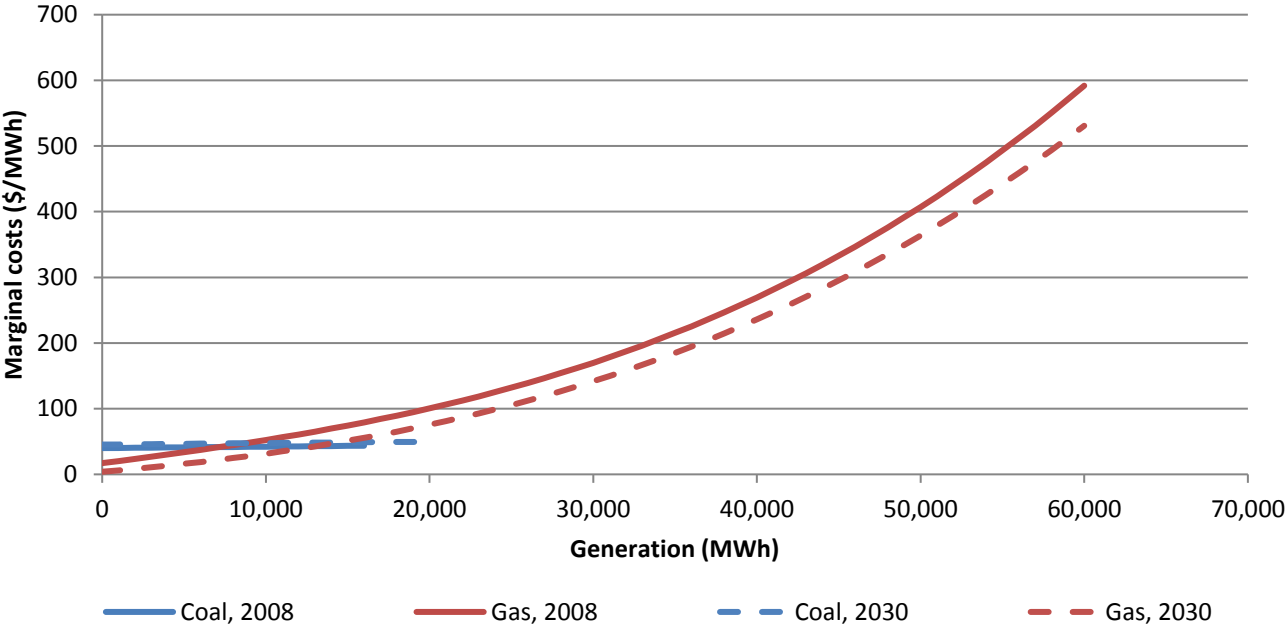


Figure 3. Marginal cost curves for coal and natural gas, 2008 and 2030



**Figure 4. Generation change caused by 2 percent demand increase:
coal and natural gas**

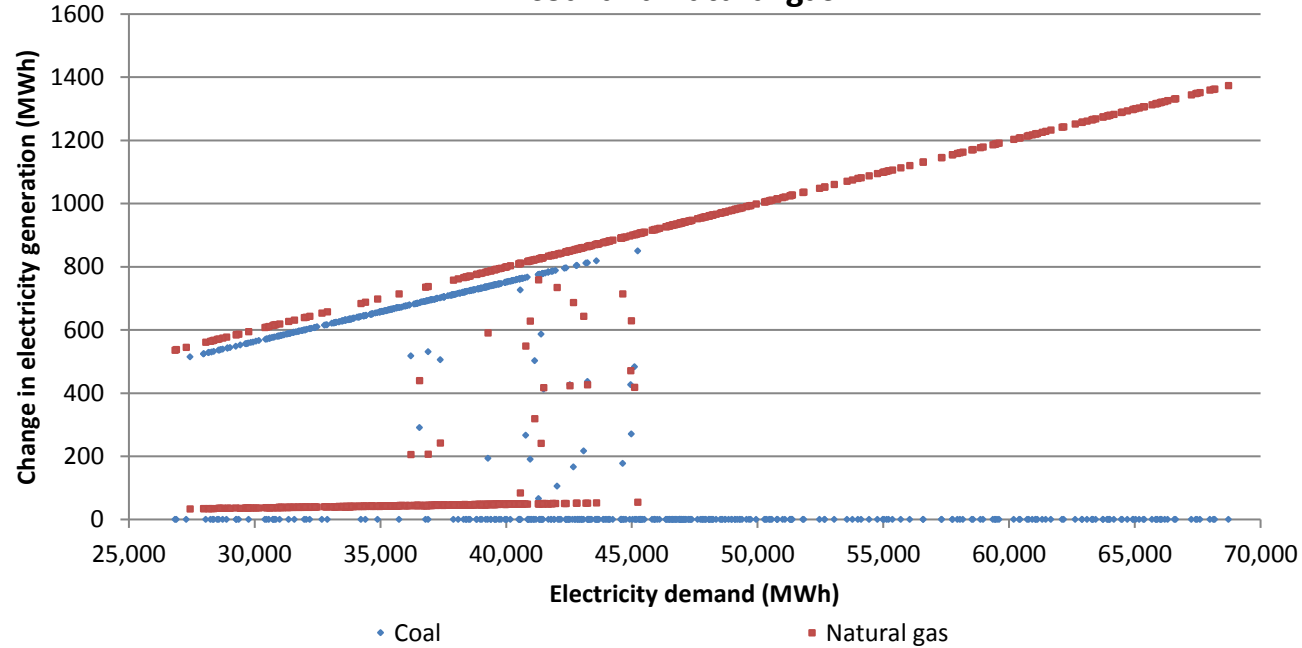


Figure 5. Effects of storage costs on equilibrium outcomes, without wind or solar investment

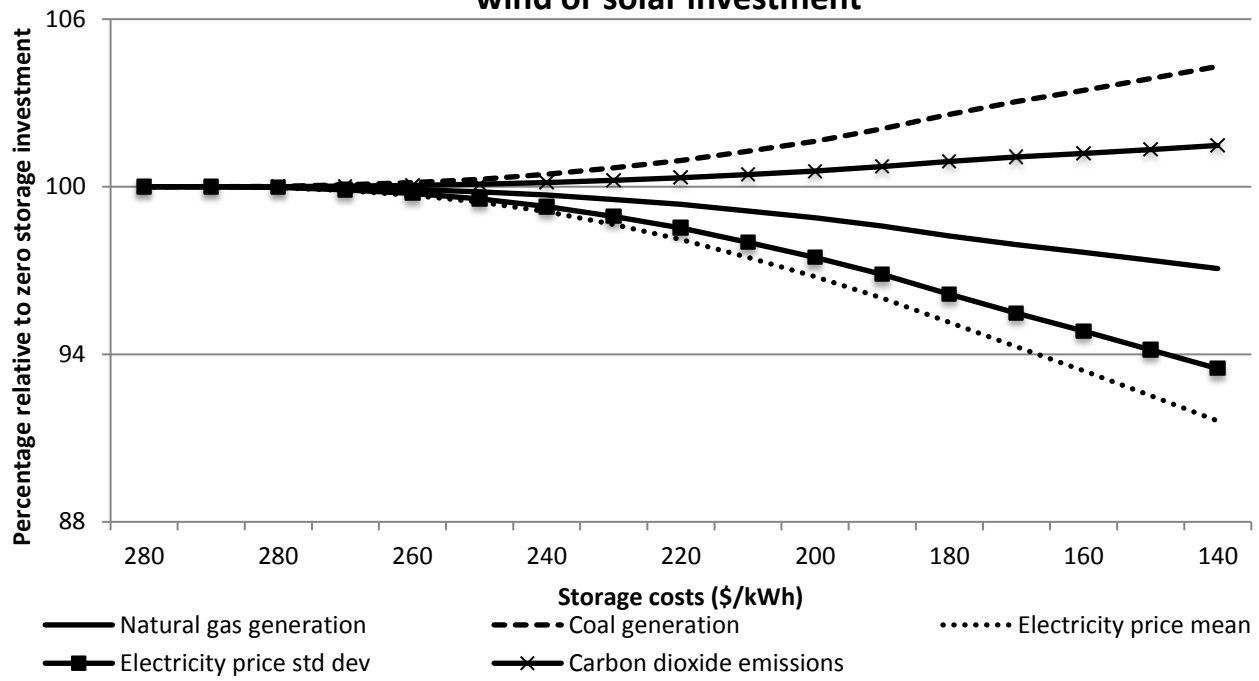
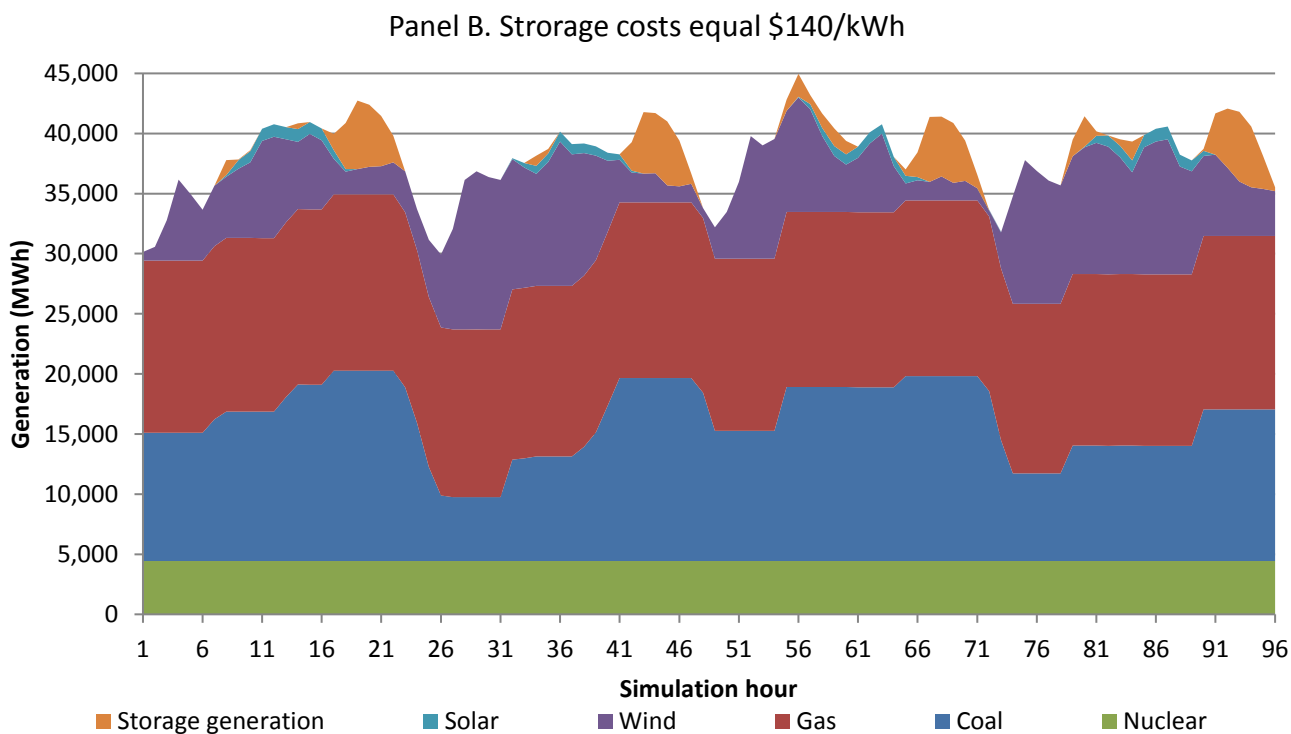
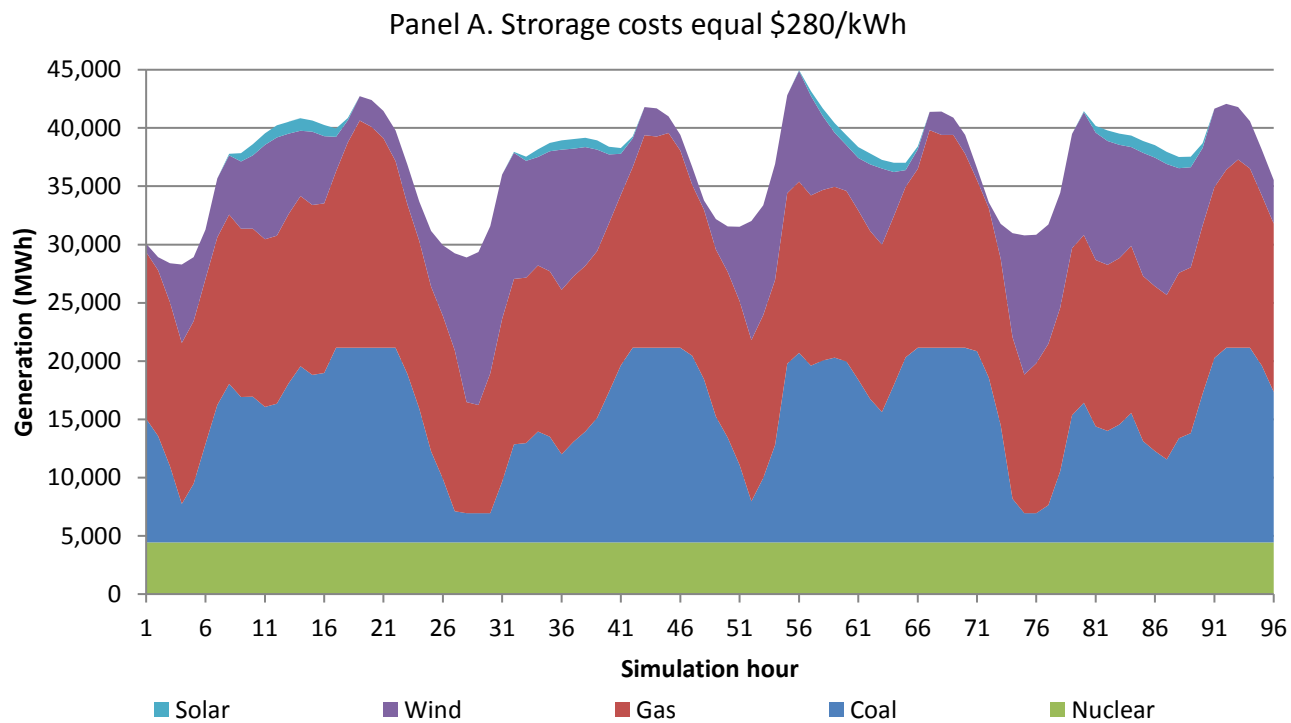


Figure 6. Hourly generation by fuel type, without wind or solar investment



**Figure 7. Generation change caused by 2 percent demand increase:
coal, natural gas, and wind**

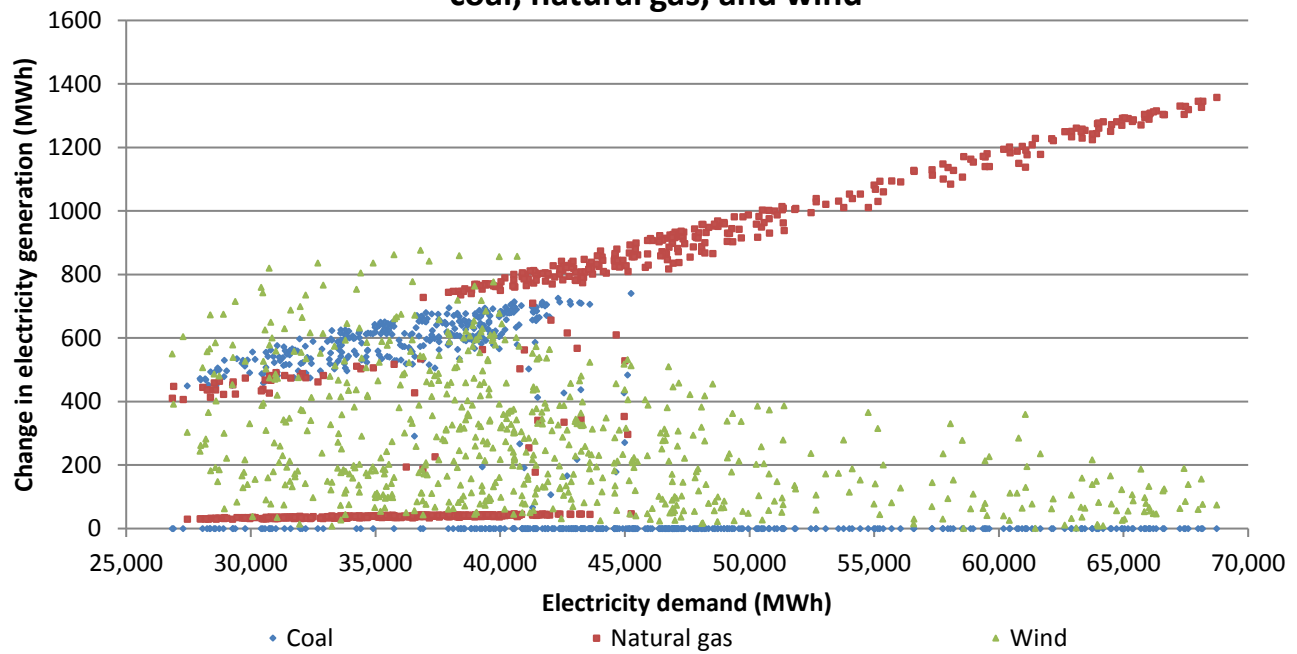
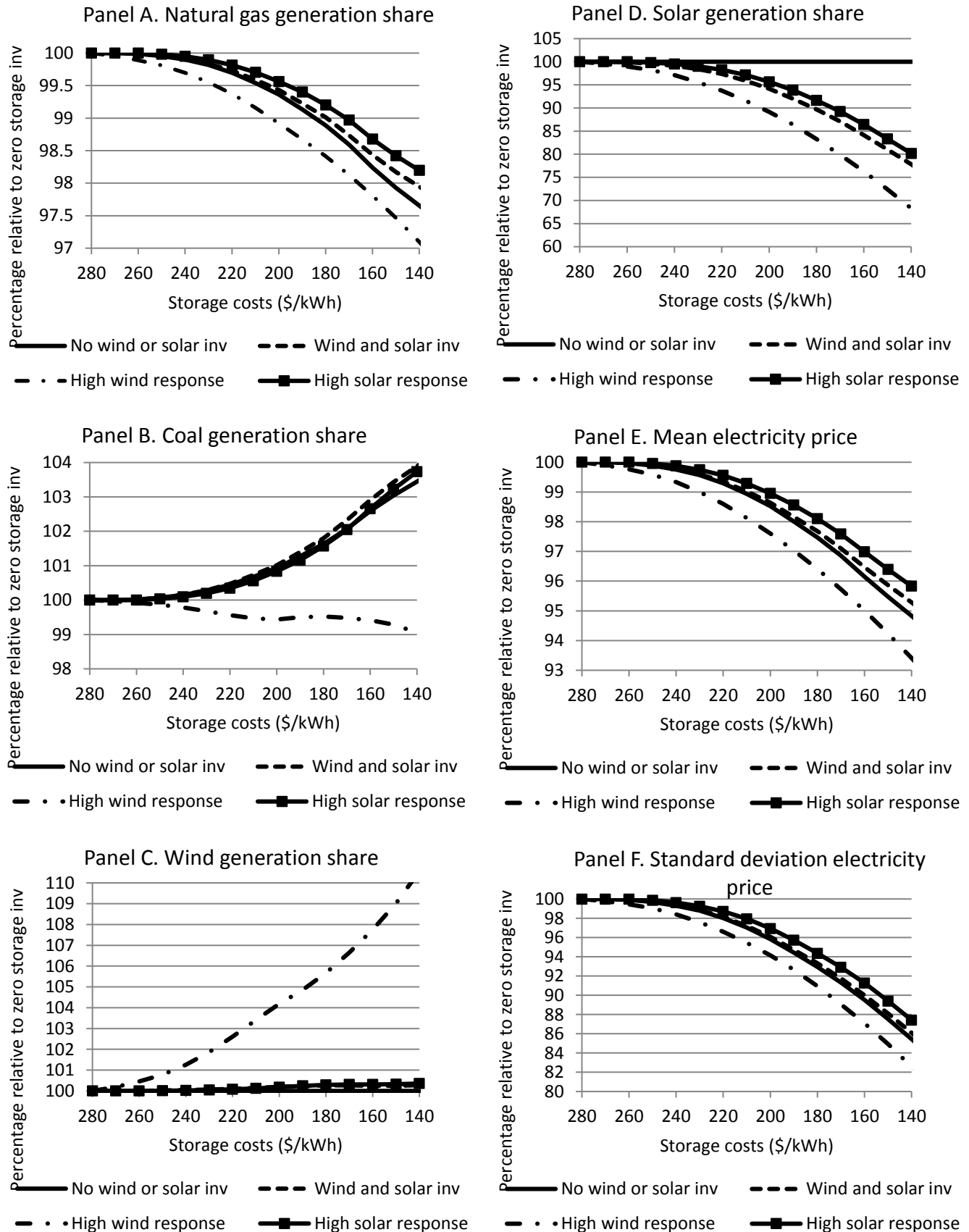


Figure 8. Effects of storage costs with wind and solar investment



Panel G. Carbon dioxide emissions

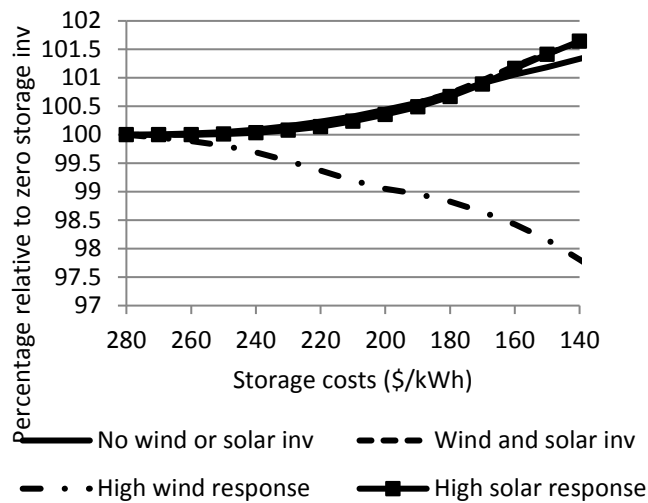


Figure 9. Hourly generation by fuel type, with wind and solar investment

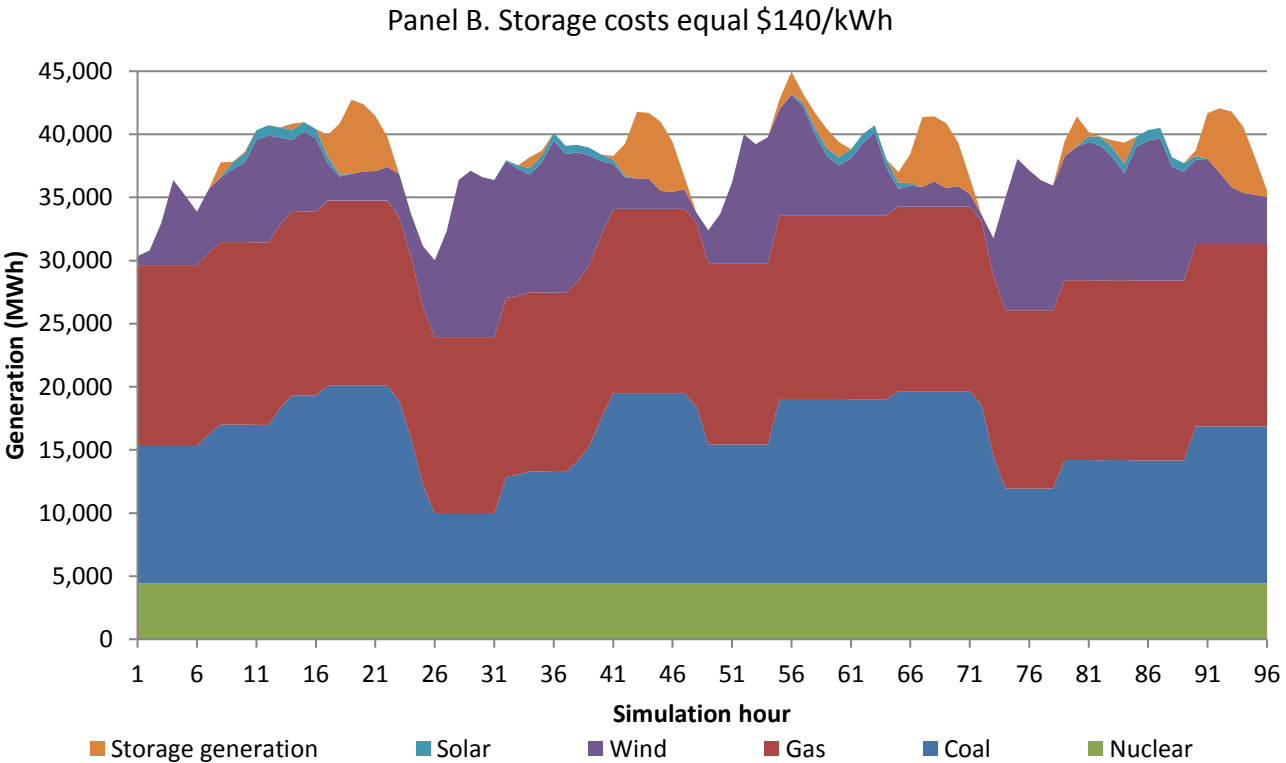
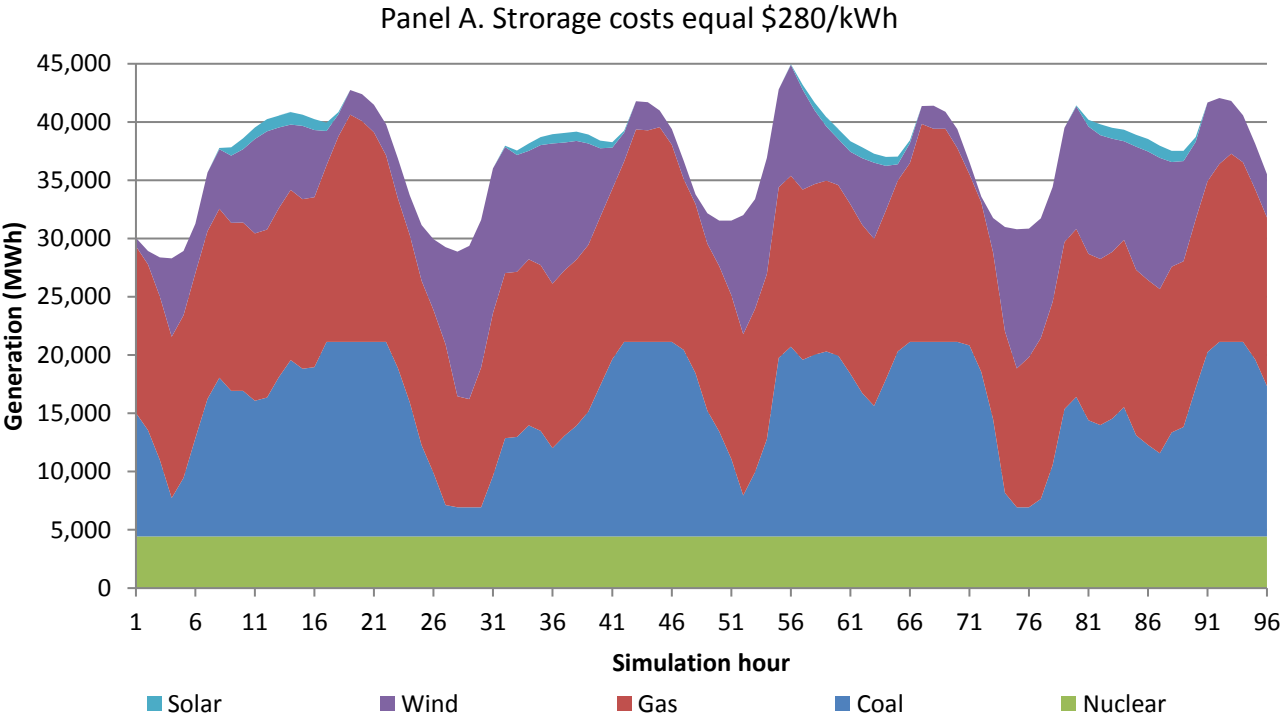


Figure 10. Effect of carbon tax on coal and natural gas responses to demand increase

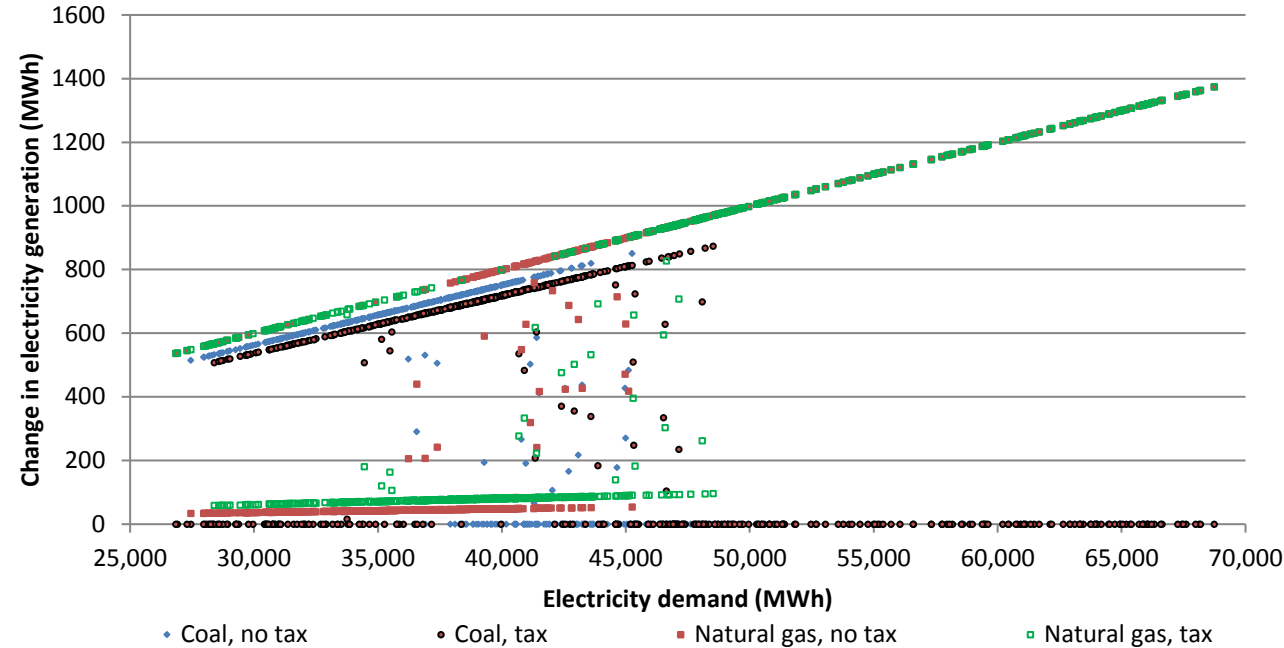


Figure 11. Effects of storage costs on equilibrium outcomes, with carbon tax

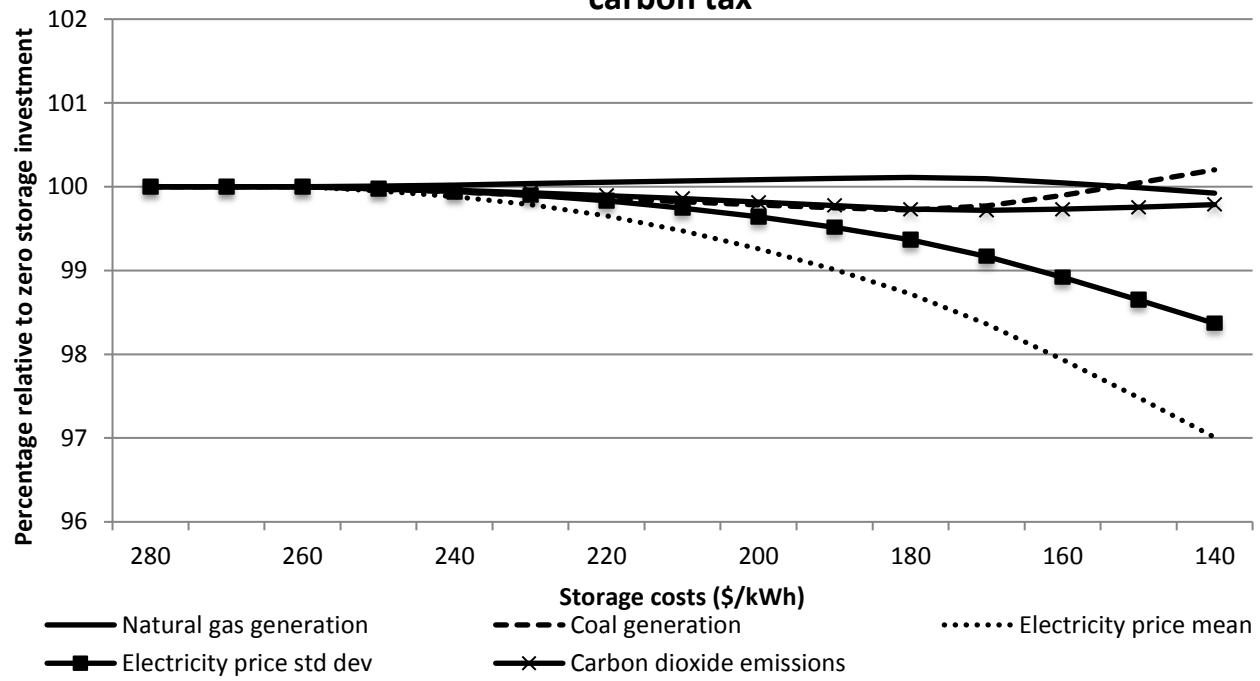


Table 1. Effects of fuel prices and demand on wind investment

	(1)	(2)	(3)	(4)	(5)
	<u>Dependent variable: wind investment (MW)</u>				
Log natural gas price	253.56 (135.48)	144.04 (239.69)	250.92 (140.62)	111.91 (191.79)	1521.34 (692.09)
Log coal price	564.96 (272.85)	498.66 (207.68)	530.97 (418.41)	28.15 (463.88)	3389.74 (1575.41)
Log ERCOT generation	6.81 (117.38)	15.47 (103.23)	15.97 (142.32)	-9.06 (110.73)	40.87 (650.85)
PTC unavailable	-123.90 (51.63)	-120.88 (50.57)	-118.66 (69.86)	-129.60 (51.98)	-743.42 (287.34)
Log (natural gas / wind capital costs)			-40.42 (304.67)		
Number of observations	120	120	120	120	20
R squared	0.29	0.30	0.29	0.31	0.49
Forecasted prices and demand?	No	Yes	No	No	No
Time trend?	No	No	No	Yes	No
Aggregate across ERCOT?	No	No	No	No	Yes

Notes : The table reports coefficient estimates with standard errors in parentheses, which are robust to heteroskedasticity. The dependent variable is wind investment in megawatts (MW). Observations are by PCA and year in columns 1-4 and by year in column 5. PTC expiration year is a dummy variable equal to one if the PTC expired in the corresponding year. Column 2 includes forecasted fuel prices and demand in place of current fuel prices and demand. Column 3 includes the log of the ratio of the estimated capital costs for a new combined cycle plant to the capital costs for a new wind plant, from EIA. Column 4 includes a linear time trend.

Table 2. ERCOT summary statistics and simulation outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	2004		2008		2010	
	<u>Panel A. Capacity (GW)</u>					
Nuclear	5.1		5.1		5.1	
Coal	16.5		16.4		18.9	
Natural gas	59.0		60.1		57.3	
Wind	1.2		6.8		9.2	
	<u>Panel B. Fuel prices (\$/mmBtu)</u>					
Coal	1.3		1.6		2.0	
Natural gas	5.8		8.8		4.6	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
	<u>Panel C. Percentage generation</u>					
Nuclear	12.9	13.6	12.2	13.2	12.2	13.0
Coal	37.5	41.9	35.1	43.3	35.6	33.2
Natural gas	48.7	43.4	48.3	37.4	45.0	45.6
Wind	0.9	1.1	4.5	6.1	7.1	8.1
	<u>Panel D. Electricity prices (\$/MWh)</u>					
Mean	45	52	72	70		54
Standard deviation	24	33	69	41		27
	<u>Panel E. Carbon dioxide emissions intensity of coal and gas generation (tons/MWh)</u>					
Emissions intensity	0.69	0.71	0.68	0.72	0.68	0.67

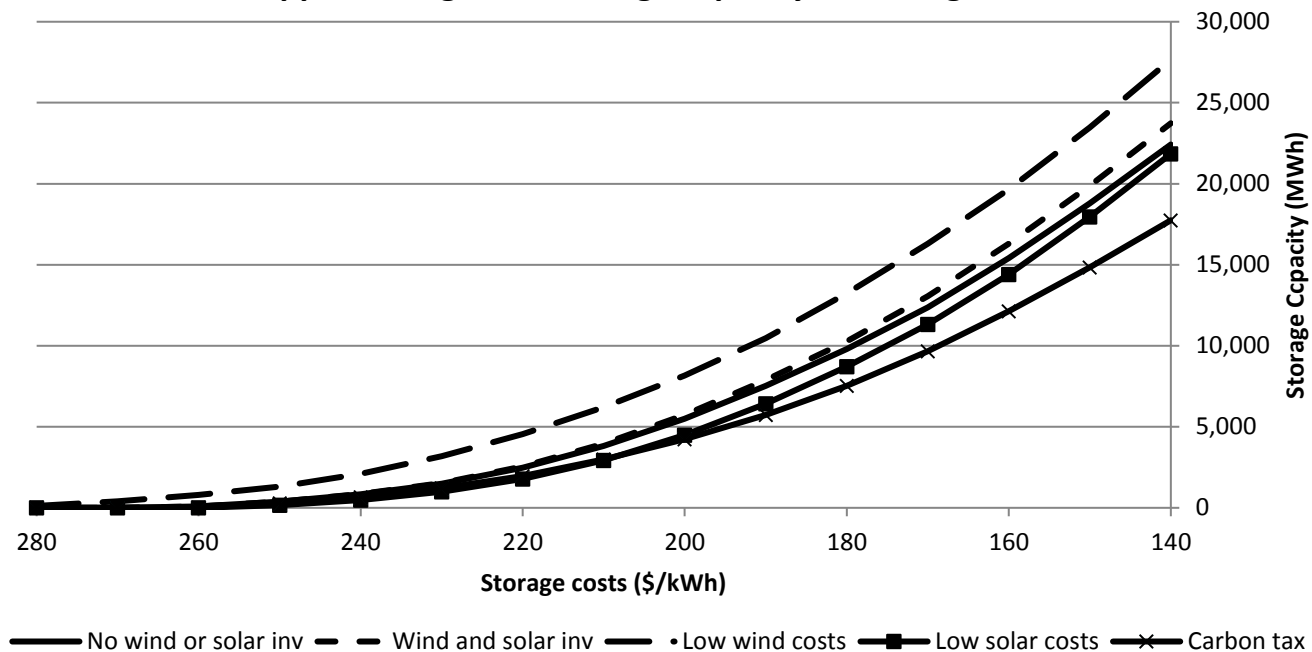
Notes : Panel A reports capacity levels from EIA and Panel B reports fuel prices from EIA. Panel C reports the observed and simulated generation shares, with observed levels from EIA. Panel D compares observed and simulated electricity prices, with observed prices from ERCOT. Panel E compares observed and simulated rates of carbon dioxide emissions per coal and gas-fired generation, with observed values from EIA and using EIA emissions factors.

Table 3. Simulation results by scenario, without storage investment

	(1)	(2)	(3)	(4)	(5)
	No wind or solar investment	Wind and solar investment	Low wind costs	Low solar costs	Carbon tax
Natural gas generation	0.45	0.45	0.43	0.45	0.49
Coal generation share	0.31	0.31	0.28	0.31	0.24
Wind generation share	0.12	0.12	0.18	0.12	0.14
Solar generation share	0.014	0.014	0.012	0.019	0.020
Mean electricity price (\$/MWh)	78	78	73	77	98
Standard deviation electricity price (\$/MWh)	57	57	57	56	52
Carbon dioxide emissions rate (tons/MWh)	0.48	0.48	0.44	0.47	0.42

Notes : The table reports outcomes for the scenarios indicated in the column headings with zero storage investment.

Appendix Figure 1. Storage capacity vs. storage costs



Appendix Figure 2. Conceptual Study Domain

