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The private and social economics of bulk electricity storage

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ABSTRACT

The ability to store excess intermittent renewable electricity is increasingly being seen as a key option for integrating large quantities of renewable capacity. However, intermittent energy sources currently account for very small amounts of total generation. Despite this fact, policymakers have begun implementing requirements that will dramatically increase the amount of bulk storage capacity. This paper examines the social benefits provided by bulk storage in the Texas electricity market, which has a large amount of renewable capacity relative to other states, but still quite limited renewable penetration. We focus on the impact of arbitraging electricity across time—a major service of bulk storage. Using current storage technologies, we demonstrate that electricity arbitrage will increase daily CO_2 emissions by an average of 0.19 tons for each MWh stored. In addition, daily SO_2 emissions will increase by an average of 1.89 pounds/MWh while NO_X emissions will fall by an average of 0.15 pounds/MWh.

1. Introduction

Maintaining the stability of an electric grid requires continuously equating the quantity of electricity supplied with the quantity of electricity demanded. Accomplishing this task is complicated because the short-run demand for electricity is extremely inelastic and constantly shifting over time. To meet the level of electricity demanded, suppliers have typically depended on fossil fuels which can be burned to create electricity when needed. However, concerns over the environmental impacts of fossil fuel combustion are driving a shift toward greater use of renewable energy sources (*e.g.*, wind, solar), which, unlike fossil fuels, are often available only intermittently.

In systems with large amounts of intermittent renewable capacity, the ability to store excess renewable output is seen as a key option for overcoming the grid stability issues posed by the intermittency of renewable generation (Swider, 2007; Black and Strbac, 2007; Abbey and Joos, 2007; Succar and Williams, 2008). Recent articles in *Science* (Dunn et al., 2011) and *The Economist* highlight the potential benefits of electricity storage, with *The Economist* article going as far as stating, "Better ways of storing energy are needed if electricity systems are to become cleaner and more efficient."[1] While it is certainly true that storage can play a vital role in balancing supply and demand in markets with substantial intermittent generation, most regions currently have very limited levels of intermittent renewable output. In 2011, generation from wind and solar energy only accounted for 3% of total U.S. electricity production.[2] In the Texas market, which leads the U.S. in intermittent generation, less than 8% of total output came from intermittent sources.[3]

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[1] "Packing Some Power." The Economist, March 3, 2012. http://www.economist.com/node/21548495
[2] Information on electricity generation by source is provided by the U.S. Energy Information Administration.
[3] Data on the total generation in the Texas Market is provided by ERCOT, the independent system operator that oversees the market.

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Despite the limited penetration of intermittent renewables, policymakers have begun to advocate for sizable increases in storage capacity. For example, California recently passed Assembly Bill 2514, the "Energy Storage Portfolio", which will require utilities in the state to procure a minimum level of storage capacity. Similar policies at the federal level, such as the proposed STORAGE Act of 2009 and the STORAGE 2010 Act, have received support as well. In addition, several states have begun to include electricity storage units in the list of qualified technologies which can be used to satisfy their Renewable Portfolio Standards (RPS).[4]

Inducing capacity investments in nascent storage technologies can spur learning which provides long-run cost reductions. These cost reductions may prove to be beneficial down the road, once renewables reach levels that necessitate storage. However, to evaluate policies designed to jump-start storage investment, it is crucial to consider the costs and benefits incurred by incorporating storage into current markets, which have limited renewable capacity. An extensive engineering literature examines a variety of benefits provided by storage, ranging from improved reliability to reduced transmission requirements. However, very little attention is paid to the impact storage has on pollution—a key determinant of the social benefit of storing electricity. This paper seeks to begin to fill that gap by exploring the private and external benefits provided by a major use of storage, arbitraging electricity across time.

Using a simple, two-period model of a competitive electricity market, we first analytically examine the private and social benefits of electricity arbitrage. In regions with low to reasonably high levels of renewable capacity, we demonstrate that short-run renewable output is unaffected by electricity arbitrage.[5] Instead, arbitrage increases production from the conventional generators on the margin during the low demand (off-peak) periods and decreases generation from the marginal conventional units during the high demand (peak) periods. If the emission rates of the off-peak marginal generators are not less than the peak period marginal emission rates, arbitraging electricity will increase pollution, reducing the social benefit of arbitrage.

In addition, we use the simple model to explore how increased arbitrage alters the benefits provided by renewable capacity. By replacing a portion of peak period electricity generation with increased off-peak production, electricity arbitrage will push off-peak wholesale prices up and peak prices down. In most regions, off-peak periods typically occur during the early morning while the peak demand occurs during the afternoon. Therefore, output from renewable generators which produce most heavily overnight (*e.g.*, many wind turbine installations) will become more valuable with increased arbitrage. Conversely, the value of electricity from renewables that produce during the daytime (*e.g.*, solar) will fall with increased arbitrage. While previous research highlights that storage can be a vital complement to intermittent generators in markets with substantial levels of intermittent renewable capacity, our analytical results demonstrate that in our current electricity markets, increased storage capacity can in fact reduce the value of renewable generation.

To examine the magnitude of the potential impact of arbitrage on emissions, we simulate the effect a marginal increase in arbitrage will have on electricity production in the Texas electricity market. The Texas region serves as an ideal market for this study because the regional grid is very isolated. Therefore, we can easily identify the conventional generators which will be impacted by storage. Building on the estimation strategy employed by Callaway and Fowlie (2009) and Graff-Zivin et al. (2012), we present reduced form estimates of the marginal emission rates during the daily off-peak and peak demand periods. The results reveal that marginal CO_2 and SO_2 rates are consistently higher during the off-peak hours, when arbitrage will increase generation. In contrast, the marginal NO_X rates are frequently higher during the peak hours, when arbitrage reduces generation. Therefore, our results reveal that, at the current levels of renewable capacity in the Texas market, arbitraging electricity between off-peak and peak hours will increase the daily emissions of CO_2 and SO_2 while the aggregate NO_X emissions will decrease during many months.

Our empirical results have similarities to the findings presented by Holland and Mansur (2008). Rather than studying the impact of arbitrage on emissions, these authors explore how real time electricity pricing (RTP) will affect the daily level of pollution in different regions. Much like arbitraging electricity, RTP will reduce the required generation when prices are high and increase generation when prices are low. To predict how RTP affects emissions, the authors present reduced form estimates of how the daily level of emissions is affected by within-day variance in electricity demand. Similar to the empirical results in our analysis, Holland and Mansur find that on average, reducing the within-day variance of electricity generation in the Texas market results in reductions in NO_X emissions and increases in CO_2 and SO_2 emissions.

Our empirical analysis provides two key features that are useful for exploring the benefits of electricity arbitrage. First, we flexibly estimate the marginal emission rates across different months. As a result, we are able to explore how the external costs of arbitrage vary across months. Second, using observed wholesale electricity prices, we are able to directly compare our estimates of the external costs of electricity arbitrage to estimates of the private benefits. Our results demonstrate that for plausible values of the external damage of CO_2, the social benefit of electricity arbitrage is in fact negative for much of the year.

This paper builds on previous work exploring the benefits of electricity arbitrage. Several engineer-oriented studies focus exclusively on examining the private benefits of arbitrage (Graves et al., 1999; Walawalkar et al., 2007; Sioshansi et al., 2009; Denholm and Sioshansi, 2009). Using historical wholesale electricity prices, these studies estimate the profit that can be

[4] These states include California, Hawaii, Montana, Ohio, and Utah. For a complete list of the technologies that can be used to satisfy the RPS targets, see www.dsireusa.org/.

[5] Our result formalizes an argument related to this issue put forth by Swift-Hook (2010).

earned by storing electricity when the price is low and supplying the stored energy when the price is high. However, given that emissions from the electricity sector are not efficiently priced, the social benefits provided by arbitrage will generally differ from the private benefits being estimated.

A small number of previous engineering studies have considered the external impact of storage on pollution. For example, Denholm and Kulcinski (2004) and Denholm and Holloway (2005) examine the emissions created by using alternative types of storage units coupled with different generation technologies. However, the authors only focus on the pollution created during the generation of the stored electricity and not the emissions avoided when the stored electricity is supplied. Using engineering dispatch models, Tuohy and O'Malley (2009) and Sioshansi (2011) simulate the net impact of arbitrage on emissions. While both studies highlight that emissions can potentially increase with the addition of storage, the simulated impacts on pollution are sensitive to the modeling assumptions.[6] For example, Sioshansi shows the magnitude of the change in emissions, and, in some cases, even the sign on the change in emissions depends on the assumed level of competition in the market.

This paper contributes to the literature by presenting transparent, empirical estimates – as opposed to simulation based estimates – of the full social value of electricity arbitrage. Our results reveal that in the Texas electricity market, the marginal social benefits of electricity arbitrage are substantially lower than the marginal private benefits. These findings highlight that, given the current low levels of renewable capacity, public policies designed to increase storage capacity may not be justified at this point in time on the basis of their short to moderate term impact on social welfare

The remainder of the paper proceeds as follows. Section 2 briefly reviews the various storage technologies and discusses the potential for growth in bulk electricity storage capacity. Section 3 presents a two-period model of a competitive electricity market to demonstrate how electricity arbitrage can affect aggregate pollution levels as well as the value of renewable capacity. Section 4 describes the regional electricity market studied in the empirical application. Section 5 presents the estimates of the marginal emission rates during the off-peak and peak periods. Section 6 uses the empirical results to simulate the impact of marginal increases in electricity arbitrage on aggregate pollution. Section 7 concludes.

2. Electricity storage technologies

This section provides a brief overview of the different types of electricity storage systems and the functions they can serve when embedded within an electricity market. We pay specific attention to bulk storage technologies, the primary technology used for arbitraging electricity and the focus of most government policies.

2.1. Categorization of storage technologies

Electricity is typically stored in three broad ways: as potential energy, kinetic energy, or chemical energy.[7] An example of a technology that stores electricity as potential energy is pumped hydroelectric storage (PHS). Electricity from a grid can be used to pump water from a low reservoir to a higher reservoir. At a later point in time, the water can be released back downhill through a turbine, generating electricity. A measure commonly used to describe the efficiency of electricity storage units is the ‘roundtrip’ efficiency. The roundtrip efficiency is the ratio of the quantity of electricity that can be supplied by a storage unit divided by the quantity of electricity initially stored. Due to energy losses that occur while pumping water uphill, as well as losses that occur when re-generating electricity, typical PHS units have roundtrip efficiencies ranging from 76% to 85% (Rastler, 2010).

Another technology that stores electricity in the form of potential energy is compressed air energy storage (CAES). CAES units use electricity from a grid to compress air, typically in underground caverns, which can then be released at a later point in time and used to co-power a turbine. Estimates of CAES units' roundtrip efficiencies typically range from 77% to 89% (Succar and Williams, 2008).

Different from potential energy, electricity can be stored in the form of kinetic energy. For example, electricity from a grid can be used to rotate a flywheel that continues to spin with very little friction. When electricity is needed, the spinning flywheel can be used to generate electricity. Finally, electricity can be converted to chemical energy and stored in batteries.[8] Regardless of whether a storage unit stores electricity as potential, kinetic, or chemical energy, the storage technologies can be coarsely divided along two dimensions. The first is the power the storage unit can provide. Power is measured in terms of Watts (*e.g.*, Kilowatts, Megawatts). PHS and CAES generally have the largest power ratings, often up to 100 MW or more.[9] Batteries, flywheels, and capacitors generally have lower power capacities, typically no more than a few Megawatts.

[6] In order to focus on the reliability of the electric grid, Tuohy and O'Malley assume each MW of storage capacity replaces a MW of natural gas generation capacity from the dispatch order. By altering the mix of fossil fuel units operating, this assumption will affect the simulated impacts on pollution.

[7] Additionally, electricity can be stored as thermal energy. For example, solar energy can be used to heat a material such as molten salt which then stores the thermal energy for extended periods of time. For reviews of current storage technologies available, see Denholm et al. (2010), Rastler (2010), and Dunn et al. (2011).

[8] A wide range of battery technologies are available. However, the majority are not yet at the point of being cost-competitive with the other storage technologies, although a large R&D effort is underway.

[9] For comparison, average sized natural gas fired generating plants have capacities in the range of 300 MW.

The second dimension is the duration the storage unit can supply electricity at the rated power. Many capacitors and flywheels are only capable of supplying short bursts of stored energy, on the order of seconds to minutes. Batteries can supply electricity anywhere from minutes up to multiple hours, if not days. Depending on the size of the reservoir or cavern, PHS and CAES units are capable of supplying electricity for hours at a time.

Where a storage unit lies along the power and duration dimensions plays a large role in determining the specific services the storage device can provide. Units capable of supplying small amounts of power (*i.e.* less than 1 MW) for short periods of time (*i.e.* seconds to minutes) are well suited for providing ancillary services, such as voltage or frequency regulation. However, these storage units are not capable of providing electricity for a duration long enough to participate in wholesale electricity markets. Therefore, they are not well suited for electricity arbitrage.

On the other hand, storage units capable of supplying large amounts of power (*i.e.* multiple Megawatts or more) for long periods of time (*i.e.* an hour or longer) are capable of arbitraging electricity across time. Storage technologies such as these – for example, PHS and CAES – are often referred as bulk storage units. This paper focuses on the social benefits provided by arbitraging electricity in wholesale markets using bulk storage technologies. Our goal is not to estimate the full social value of bulk storage units, which could potentially provide a number of services to an electricity market. Rather, our objective is to carefully examine the relationship between the private and social benefits of arbitrage, one of the primary uses of bulk electricity storage.[10]

2.2. Potential growth in bulk electricity storage

Currently, PHS and CAES are the most cost competitive forms of bulk electricity storage. There are 127 000 MW of capacity worldwide with PHS systems accounting for a large majority of the grid connected storage capacity.[11] The penetration of bulk storage capacity varies substantially across regions. In Europe and Japan, 10% and 15%, respectively, of the electricity delivered is supplied by storage units. In contrast, only 2.5% of the electricity consumed in the U.S. is currently supplied by storage units.

Despite the small levels of existing bulk storage capacity in the U.S., government support for both renewable electricity and electricity storage is making it increasingly important to understand the social value provided by both technologies. Currently, 29 states have adopted binding RPS's which set targets for renewable electricity shares as high as 40 %. In addition, a variety of federal subsidies and tax credits are available for renewable producers.[12] Combined, these policies have caused a rapid increase in the quantity of renewable capacity (Hitaj, 2013). Looking to the future, the growth in renewable capacity is expected to continue.[13]

Increasing electricity storage capacity is seen as a vital way to augment the benefits provided by the expansion of renewable generation. As a result, efforts to induce investment in storage are gaining momentum as well. Policies such as California's recently passed Energy Storage Portfolio, combined with sizable federal subsidies, have bulk electricity storage capacity poised for significant growth.

Where future electricity bulk storage units are located will have a large impact on the value they provide.[14] Graves et al. (1999), Walawalkar et al. (2007), and Sioshansi et al. (2009) highlight that the private returns to arbitrage will vary across markets based on regional variation in the differences between off-peak and peak prices. In addition, if transmission constraints exist within a regional market, where the storage unit is embedded will affect which services the storage unit can provide. For example, several studies explore the cost effectiveness of combining bulk storage units with intermittent generators located in regions with transmission constraints (Cavallo, 1995; DeCarolis and Keith, 2006; Greenblatt et al., 2007). These studies find that the storage units will reduce the investments in transmission capacity that are required to transport renewable generation to demand centers.

The remainder of this paper examines the value of bulk storage in the case where transmission constraints do not exist. Denholm and Sioshansi (2009) point out that there is a tradeoff between installing bulk storage units near demand centers versus locating them near transmission constrained renewable sources. While siting the storage with intermittent renewables will reduce the amount of curtailed output, the private arbitrage value of storage units is maximized by siting them near demand centers where transmission constraints will not limit access to wholesale markets. In order to compare the private and social benefits of arbitrage, we focus on the use of bulk storage units which maximize private returns.

[10] Rastler (2010) compares the private returns to a variety of services that can be provided by electricity storage. Our analysis focuses on arbitrage, which is one of the primary sources of revenue for bulk storage units. In addition, Sioshansi and Denholm (2010) highlight that unlike the private returns to arbitrage, the private value of participating in ancillary service markets declines rapidly as storage capacity increases.

[11] For information on storage capacity, see Mears et al. (2003).

[12] For information on federal subsidies and state RPS policies, see www.dsireusa.org.

[13] The Energy Information Administration's "*Annual Energy Outlook 2010*" predicts renewable generation will account for 45–65% of the increase in total U.S. generation between 2008 and 2035.

[14] While batteries can be installed in any location, both PHS and CAES units require specific geological characteristics. PHS requires access to water and elevation differences. While many of the ideal locations have PHS systems already in place, there is still room for growth in PHS capacity. For example, a PHS unit is being installed by San Diego Gas & Electric in Southern California. The storage unit will provide 40 MW for up to 10 h. In addition, Succar and Williams (2008) find that 75% of the U.S. has ground formations suitable for CAES units.

3. Two-period model

In this section, we present a simple two-period model of a competitive, wholesale electricity market. The model highlights which factors determine the magnitudes of the marginal private benefits and marginal social benefits of electricity arbitrage. We demonstrate that, in the presence of unpriced emissions, there is generally a gap between the private and social benefits of arbitrage. Additionally, we use the model to demonstrate the conditions under which arbitrage will increase or decrease the returns to renewable capacity investments.

3.1. Competitive electricity market

Consider a competitive wholesale electricity market in which electricity is supplied in two distinct periods. Period one is the "off-peak" period and period two is the "peak" period. Demand in each period is perfectly inelastic and the off-peak demand, D_o, is strictly less than the peak demand, D_p. Electricity is generated using two technologies: conventional generators, which can be dispatched on command (*e.g.*, coal, natural gas, nuclear, hydroelectric), and intermittent renewable generators (*e.g.*, wind, solar).

The aggregate generation from conventional sources during period $t=\{\text{o},\text{p}\}$ is given by G_t. The private costs of producing G_t is given by $c(G_t)$, which is assumed to be strictly increasing and convex. These assumptions imply that conventional generators are dispatched in increasing order of their marginal private costs.

In addition to the private generation costs, conventional generators produce a negative externality, unpriced pollution. The aggregate level of pollution emitted by conventional generators in a single period is given by $e(G_t)$, which is assumed to be weakly increasing, however, no restrictions are placed on the second derivative of the pollution function.[15] Therefore, the emission rates of the conventional generating units on the margin at low levels of G_t can be greater or less than the emission rates of the units on the margin at higher levels of G_t. The marginal external cost of pollution is assumed to be constant and equal to τ.[16]

The aggregate level of generation from renewable sources during period t is given by R_t. To produce electricity from renewables, only a fixed cost and regular maintenance expenditures must be paid. The marginal generation cost is zero and no emissions are created from the intermittent renewable generation. Unlike production from conventional sources, intermittent renewable generation cannot be dispatched on command. The output in period t is equal to the product of the installed renewable capacity, K, and the capacity factor, x_t, which is bounded between 0 and 1. For simplicity, we assume that the off-peak and peak capacity factors, as well as the off-peak and peak demands, are non-random constants. To study other benefits of storage – for example, improved supply reliability or frequency regulation – much more sophisticated modeling of intermittency and demand uncertainty must be modeled. However, for our focus on the value of arbitrage, assuming the values for (x_o, x_p, D_o, D_p) are constant does not affect the intuition provided by the exercise.

We explore the impact of storage in markets where the level of renewable penetration is not large enough to force renewable output to be curtailed. Therefore, we assume that demand exceeds the maximum renewable generation in each period, $D_t > K$. Without loss of generality, we additionally assume that $D_p - K\cdot x_p > D_o - K\cdot x_o$. This ensures that the profit maximizing storage owners will optimally purchase electricity during the off-peak period and supply electricity during the peak period.[17]

In addition to the conventional and intermittent renewable generators, we introduce a third technology, an electricity storage sector. Storage owners can arbitrage electricity across periods by demanding electricity during the initial off-peak period and supplying the stored electricity during the peak period. The quantity of electricity stored off-peak is given by S_o. During the process of charging and discharging, a portion, $\alpha \in [0,1]$, of the electricity is lost. The remaining electricity supplied during the peak period is equal to $(1-\alpha)\cdot S_o$.

To maintain the stability of the electric grid, the quantity of electricity demanded must exactly equal the quantity of electricity supplied during each period. Therefore, the following two conditions must hold:

$$D_o + S_o = G_o + K\cdot x_o \tag{1}$$

$$D_p = G_p + K\cdot x_p + (1-\alpha)\cdot S_o. \tag{2}$$

Given the installed renewable capacity, K, and the storage loss rate, α, Eqs. (1) and (2) define the level of conventional generation in each period as a function of the exogenous demands, exogenous capacity factors, and the quantity of electricity stored during the off-peak period.

[15] The level of emissions is not strictly increasing in G_t due to the fact that non-polluting dispatchable sources (*e.g.* hydroelectric) can potentially be the marginal source of electricity.

[16] While a variety of pollutants are emitted during the combustion of fossil fuels, our theoretical model uses a single aggregate measure of pollution. To the extent that the marginal damage varies across pollutants, and varies based on where the pollutants are emitted, the measure e can be thought of as the weighted sum of the various pollutants, where the weights are determined by marginal external damage of each pollutant. For a pollutant with a higher marginal social cost, each unit of pollution emitted will contribute a larger amount to the overall level of e.

[17] If we instead assume, $D_p - K\cdot x_p < D_o - K\cdot x_o$, then we can simply reverse the order of period's one and two and the conclusions will remain unchanged.

3.2. Marginal social benefits of arbitrage

To determine the social benefit of electricity arbitrage, we examine the impact a marginal increase in storage has on the total cost of generating electricity. Over the two periods, the social cost of supplying electricity is given by the following expression:

$$TC = c(G_o) + c(G_p) + \tau \cdot [e(G_o) + e(G_p)], \tag{3}$$

where G_o and G_p are defined by Eqs. (1) and (2), respectively. The social benefit of a marginal increase in storage is equal to the reduction in total costs, $MSB(S_o) = -\partial TC/\partial S_o$.

To solve for $MSB(S_o)$, we must determine the impact of storage on conventional generation. Panels A1 and A2 of Fig. 1 illustrate the off-peak and peak equilibriums. In both periods, renewable generation is not the marginal energy source, $R_o < D_o$ and $R_p < D_p$. Therefore, storing electricity during the off-peak period effectively shifts the demand curve outwards (Panel A1), increasing conventional generation by S_o units. Resupplying the stored energy during the subsequent peak period shifts the aggregate supply curve outwards (Panel A2), reducing conventional generation by $(1-\alpha) \cdot S_o$ units.

Taking the derivative of Eq. (3), with respect to S_o, yields the following expression for the marginal social benefit of storing off-peak electricity:

$$MSB(S_o) = (1-\alpha) \cdot c'(G_p) - c'(G_o) + \tau \cdot [(1-\alpha) \cdot e'(G_p) - e'(G_o)], \tag{4}$$

where G_o and G_p are defined by Eqs. (1) and (2). Under the assumption that the market is perfectly competitive, the market clearing price in each period will equal the private marginal cost of supplying electricity: $P_o = c'(G_o)$ and $P_p = c'(G_p)$. Substituting the prices into Eq. (4), the marginal social benefit of storage can be expressed as the sum of the marginal private benefit and the marginal external benefit:

$$MSB(S_o) = \underbrace{(1-\alpha) \cdot P_p - P_o}_{\text{Marginal Private Benefit}} + \underbrace{\tau \cdot [(1-\alpha) \cdot e'(G_p) - e'(G_o)]}_{\text{Marginal External Benefit}}. \tag{5}$$

The first term in Eq. (5) is the marginal private benefit of an additional unit of S_o. If $(1-\alpha) \cdot P_p > P_o$, storage owners will earn positive marginal profits.

The second term in Eq. (5) represents the external benefit of a marginal increase in S_o. This term is equal to the product of the marginal external cost of pollution, τ, and the decrease in pollution from a marginal increase in S_o. If $e'(G_o)/e'(G_p) > (1-\alpha)$, then the aggregate emissions increase with additional storage.

Panels B1 and B2 of Fig. 1 illustrate the case where arbitrage increases the aggregate level of emissions. In addition to the demand and marginal generation cost curves, the graphs also display the marginal external damage curve, $\tau e'(G)$. In this example, the initial off-peak marginal emission rate, $e'(G_o)$, exceeds the peak period marginal emission rate, $e'(G_p)$. Therefore, regardless of the loss factor α, the increase in emissions caused by storing electricity during the off-peak period (Panel B1) will be larger than the decrease in emissions caused by resupplying the stored electricity during the peak period (Panel B2). In this case, the marginal social benefit of arbitrage will be less than the marginal private benefit.

3.3. Impact on the value of renewable electricity

In addition to identifying the direct social benefit of arbitraging electricity across periods, we use our simple model to examine the impact of arbitrage on the value of intermittent renewable capacity. In the short-run, the social benefit of a marginal increase in renewable capacity is equal to the avoided costs, $MSB(K) = -\partial TC/\partial K$, where the total costs are given by Eq. (3). Taking the derivative of the total cost with respect to K yields the following expression for the marginal social benefit:

$$MSB(K) = c'(G_p) \cdot x_p + c'(G_o) \cdot x_o + \tau \cdot [e'(G_p) \cdot x_p + e'(G_o) \cdot x_o], \tag{6}$$

where G_o and G_p are defined by Eqs. (1) and (2), respectively. The marginal social benefit of renewable capacity can again be split into the marginal private and marginal external benefits. Continuing to assume the equilibrium prices are equal to the marginal generation costs, the marginal private benefit is equal to the prices weighted by the additional renewable generation in each period, $MPB(K) = P_p \cdot x_p + P_o \cdot x_o$. The marginal external benefit is equal to the social cost of the avoided pollution, $MEB(K) = \tau \cdot [e'(G_p) \cdot x_p + e'(G_o) \cdot x_o]$.

To determine how arbitrage affects the value of renewable capacity, we examine the impact a marginal increase in off-peak storage has on $MSB(K)$. Taking the derivative of Eq. (6) with respect to S_o results in the following expression:

$$\frac{\partial MSB(K)}{\partial S_o} = \overbrace{c''(G_o) \cdot x_o - (1-\alpha) \cdot c''(G_p) \cdot x_p}^{\partial MPB(K)/\partial S_o} + \underbrace{\tau \cdot [e''(G_o) \cdot x_o - (1-\alpha) \cdot e''(G_p) \cdot x_p]}_{\partial MEB(K)/\partial S_o}, \tag{7}$$

where G_o and G_p are defined by Eqs. (1) and (2), respectively.

Eq. (7) highlights that an increase in arbitrage can increase or decrease the private benefit of renewable capacity. A marginal increase in S_o will increase the off-peak price by $\partial P_o/\partial S_o = c''(G_o)$ and decrease the peak price by

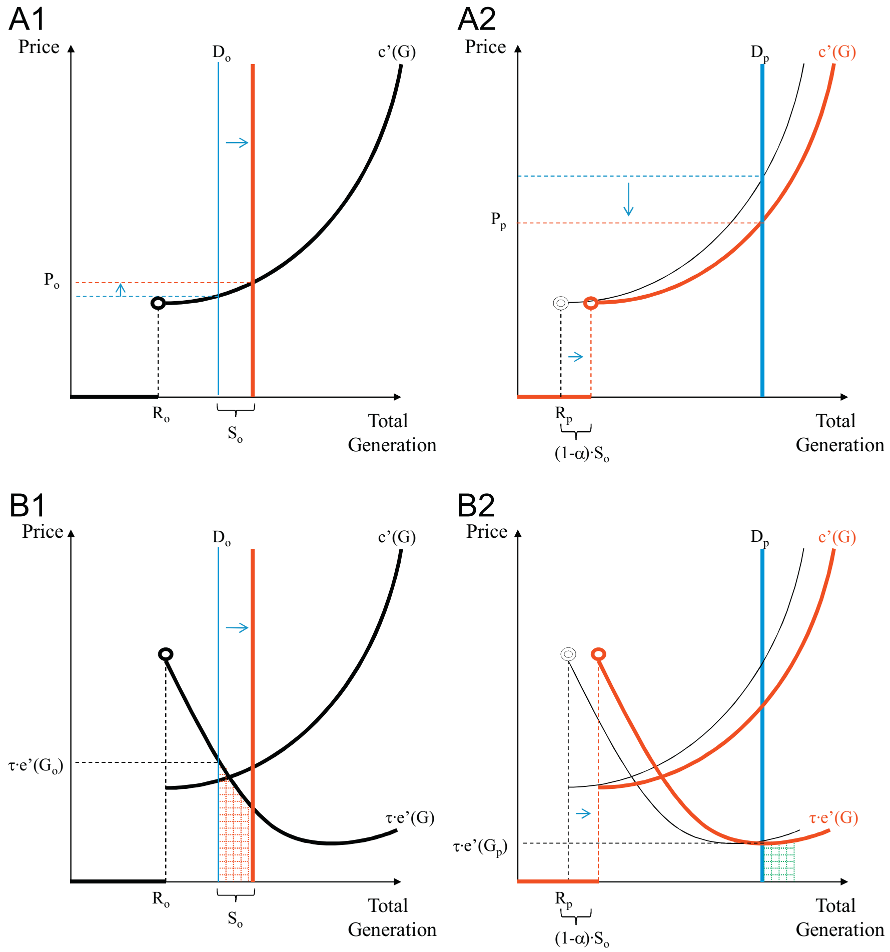

Fig. 1. Two-period model of the impact of arbitrage. (A1) Off-Peak Period Equilibrium, (A2) Peak Period Equilibrium, (B1) Off-Peak Emissions Increase and (B2) Peak Emissions Decrease.

$\partial P_p/\partial S_o = (1-\alpha) \cdot c''(G_p)$. If the following inequality is satisfied:

$$\frac{x_o}{x_p} > \frac{(1-\alpha) \cdot c''(G_p)}{c''(G_o)}, \tag{8}$$

then a marginal increase in arbitrage will increase the private returns to renewable capacity. Therefore, the private returns to a renewable generator that has larger capacity factors during the off-peak period are more likely to increase. Alternatively, the ratio of x_o/x_p will be closer to zero for a renewable technology that produces electricity more heavily during the peak, daytime hours (*e.g.*, solar). As a result, the inequality in Eq. (8) is less likely to be satisfied. Therefore, arbitrage will reduce the private value of renewables that produce more heavily during the peak period.

In addition, Eq. (7) demonstrates that arbitrage has an ambiguous impact on the external benefits provided by renewable electricity. Storing electricity off-peak, and supplying the stored energy during the peak period will alter which generating units are on the margin in each period. If $e''(G_o) < 0$, then storing electricity during the off-peak period will move a cleaner conventional generating unit onto the margin. As a result, renewable electricity supplied during the off-peak period will avoid less pollution than it would without storage. Similarly, if $e''(G_p) > 0$, supplying additional stored electricity during the peak period will again move a cleaner producer onto the margin.

The results from this simple model highlight several key points. First, in situations where the full social cost of emissions are not internalized, the marginal social benefit of electricity arbitrage will generally differ from the marginal private benefit. For the social benefits to be larger in the case where renewables are not on the margin, the peak period marginal emission rates must be sufficiently above the off-peak marginal emission rates: $e'(G_o) < (1-\alpha) \cdot e'(G_p)$. Additionally, the results demonstrate that electricity arbitrage can increase or decrease the private and external benefits of renewable capacity. The impact on the private returns to renewables depends on the pattern of renewable generation (x_o/x_p) and the price elasticity of supply at the off-peak and peak levels of conventional generation. Similarly, the impact on the external returns to renewable capacity depends on the pattern of renewable production and the shape of the marginal emission rate profile.

4. Application to Texas electricity market

The two-period model provides intuition for how the social benefits of electricity arbitrage can differ from the private benefits. To determine the magnitude of the difference between the private and social benefits, it is crucial to know the marginal emission rate when bulk storage units demand electricity, $e'(G_o)$, and the marginal emission rate when storage units supply electricity, $e'(G_p)$. The remainder of this paper explores these off-peak and peak marginal emission rates in a specific market; the Texas electricity market.

The Texas region serves as an ideal market for this analysis because the regional electric grid is very isolated. As a result, the conventional generating units which would be impacted by storage, and the pollution they emit, are easily identified. Using the intuition from the two-period model, combined with reduced form estimates of the marginal emission rates, we compare the potential marginal social benefits and marginal private benefits of electricity arbitrage in the Texas market.

The objective of the study is not to model the optimal charge and supply decisions for a bulk storage owner. Previous studies highlight that the profit maximizing charge and discharge behavior is very stable across days (Graves et al., 1999; Sioshansi et al., 2009). Electricity is consistently stored daily during the minimum price, off-peak period of the day and then discharged during the maximum price, peak period of each day. While the timing of charging and discharging is affected slightly by factors such as weekdays versus weekends, the results demonstrate that the patterns are quite steady.

Instead of modeling a dynamically optimized storage unit, we instead predict the impact of a bulk storage unit that stores electricity during the off-peak period each day and supplies the electricity during the peak period of each day. To estimate the effect on pollution, we first need to know when the off-peak and peak periods occur. Second, we need estimates of the marginal emission rates during the off-peak and peak periods. This section briefly describes the generation and emissions data used to estimate the marginal emission rates. In addition, we discuss the demand and price data used to determine when the off-peak and peak periods occur.

4.1. Generation and emissions data

The majority of the state of Texas is served by a deregulated electricity market.[18] The Electric Reliability Council of Texas (ERCOT) is the independent system operator charged with maintaining the stability of the regional transmission grid. To estimate the marginal emission rates, we use data on the hourly electricity generation and emissions in the ERCOT region between January 1, 2007 and December 31, 2009. ERCOT provides data on the hourly aggregate electricity produced by coal units, natural gas units, nuclear generators, hydroelectric units, wind turbines, and ‘other’ sources.[19] Table 1 summarizes the hourly ERCOT generation, by fuel source, over the three year period. Natural gas and coal fired generators account for 80% of the total electricity while nuclear plants produce 13% of the electricity. Intermittent output from wind turbines accounts for 5% of the total generation. Hydroelectric units and ‘Other’ sources, which include biomass, landfill gas, other fossil fuels, and solar, provide the remaining generation.

A unique feature of the Texas market is that it is not interconnected with the rest of the United States. The electric transmission grid in the United States can be thought of as three separate Interconnections: the Eastern Interconnection, the Western Interconnection, and the Texas Regional Entity. Within each Interconnection, electricity is transmitted at a synchronized frequency. To trade electricity between the Interconnections, however, electricity must either be converted from alternating current to direct current (DC) and transmitted across a limited number of DC transmission lines or be transmitted through a variable frequency transformer (VFT).[20] To simulate the impact of arbitrage in the ERCOT region, we assume that storage will not alter the flow of electricity across the DC and VFT connections.

The Environmental Protection Agency (EPA) collects data on the hourly emissions of CO_2, NO_X, and SO_2 from 276 fossil fuel fired generating units that directly supply electricity to the ERCOT market.[21] Only 10 small natural gas fired units in the region, each with a capacity below 25 MW, are not included in the EPA dataset. Therefore, the observed emissions effectively represent the total hourly pollution from the ERCOT market. Table 2 presents summary statistics for the coal and natural gas units in the EPA dataset.[22] In addition to separating the units by fuel, we further divide the natural gas fired units into ‘low’ and ‘high’ heat-rate subgroups.[23] This division is motivated by the fact that there are two broad natural gas generating technologies: cleaner combined-cycle units, which have lower heat-rates, and dirtier open-cycle units, which have higher heat-rates. We classify natural gas units with average heat-rates below 9 MMBtu/MWh as low heat-rate units and the rest as

[18] Over 85% of the electricity consumed in Texas is supplied by the deregulated market.

[19] ‘Other’ generation is the aggregate output from biomass, landfill gas, diesel, oil, and solar units. The interval generation data is available from ERCOT's Planning and Operations website; http://planning.ercot.com/

[20] During the period studied in this analysis, the maximum amount of electricity that could be traded through DC lines connecting ERCOT and the surrounding Interconnections totaled 1090 MW. In addition, a 100 MW VFT connects ERCOT with the *Comision Federal de Electricidad* (CFE) grid serving Mexico.

[21] This includes each fossil fuel unit in the ERCOT service region plus the Kiamichi Energy Facility in Oklahoma which is connected to the Texas grid.

[22] One petroleum unit in the ERCOT market is included in the EPA dataset. The emissions from this unit are included in the measure of the aggregate hourly emissions used in the empirical analysis.

[23] Heat-rate is a measure of generation efficiency. It is equal to the fuel input (in MMBtu's) divided by the level of generation (MWh's). Higher heat-rates imply less efficient generation.

Table 1
2007–2009 hourly ERCOT generation by source (MWh).

Energy source	Natural gas	Coal	Nuclear	Wind	Hydroelectric	Other
N	26 117	26 117	26 117	26 117	26 117	26 117
Mean	15 128	12 956	4681	1626	105	491
Std. Dev.	7166	1523	763	1205	96	227
Share	43.2%	37.0%	13.4%	4.7%	0.3%	1.4%

Generation data is provided by ERCOT. “Other” production is from biomass, landfill gas, oil, diesel, and solar units. Shares are equal to the total supply from each fuel source during the sample period divided by the aggregate supply.

Table 2
EPA fossil fuel unit summary statistics.

Unit type	Coal	Natural Gas (*heat-rate* <9)	Natural Gas (*heat-rate* >9)
Number of units	27	80	168
Average capacity (MW)	677	320	154
	(173)	(153)	(185)
Average heat rate (MMBtu/MWh)	10.00	7.38	11.46
	(0.66)	(1.10)	(2.06)
Average CO_2 rate (tons/MWh)	1.06	0.44	0.69
	(0.07)	(0.07)	(0.22)
Average NO_X rate (lbs/MWh)	1.44	0.31	1.67
	(0.63)	(0.55)	(1.72)
Average SO_2 rate (lbs/MWh)	6.51	0.00	0.01
	(3.67)	(0.00)	(0.05)

Emissions and gross generation data are from the EPA Continuous Emissions Monitoring Systems. Capacity data is available from the EIA-860 Generator Database. Average heat rates and emission intensities are calculated by taking the average of the individual, unit-level means. Standard deviations of unit-level means are in parentheses.

high heat-rate units. The coal units on average have the largest capacities while the high heat-rate gas units tend to be the smallest.[24]

Comparing the average heat-rates, the efficient gas fired units have lower average heat-rates than the coal units. However, over the period examined, the average monthly price of coal delivered to Texas utilities is \$1.82/MMBtu while the average price of delivered natural gas is \$6.42/MMBtu.[25] As a result, the coal fired units are typically lower on the supply curve. It is, however, important to point out that in more recent years, the price of natural gas in the U.S. has fallen closer to \$3/MMBtu. While this has made efficient natural gas units more competitive with coal fired units, the coal units are still generally dispatched ahead of units burning natural gas.

Table 2 also highlights the variation in the emission rates across generators using different fuels and technologies. Coal fired units have the highest CO_2 and SO_2 rates. Low heat-rate natural gas units have the lowest emission intensities and high heat-rate natural gas units have the highest NO_X emission rates.

4.2. Demand and market prices

Recall, in the two-period model, conventional generation is dispatched to meet the residual demand—the demand that is not met by generation from intermittent energy sources. The wholesale price of electricity is determined by the marginal cost of the conventional generator on the margin at any given time. Therefore, within a single day, the minimum price, off-peak period, and the maximum price, peak period, will occur when the residual demand is at its lowest and highest points, respectively.

To determine when the off-peak and peak hours occur in the Texas market, we use two different sources of information. First, we use the hourly residual demand in ERCOT. The residual demand is equal to the hourly quantity of electricity demanded minus the hourly generation from wind turbines.[26] Data on the hourly demand in the market is provided by ERCOT. Fig. 2 plots the average levels of demand and wind generation by hour from January, 2007 through December, 2009. On average, ERCOT demand falls to its lowest levels during the early morning hours and rises to its peak during the

[24] Unit level capacities are from the EIA-860 Generator Database.

[25] Information on the fuel prices is available from Tables 4.10.A and 4.13.A of the Energy Information Adminstration's *Electric Power Monthly*.

[26] While we would ideally be able to calculate the residual demand using all non-dispatchable output, including intermittent solar generation, data on the hourly solar generation is not available from ERCOT during the time period studied. However, given the extremely low levels of solar generation in the ERCOT market, this is not a concern. From *ERCOT's 2009 Annual Report on the Texas Renewable Energy Credit Trading Program*, generation from solar units accounted for only 0.0014% of the total ERCOT generation.

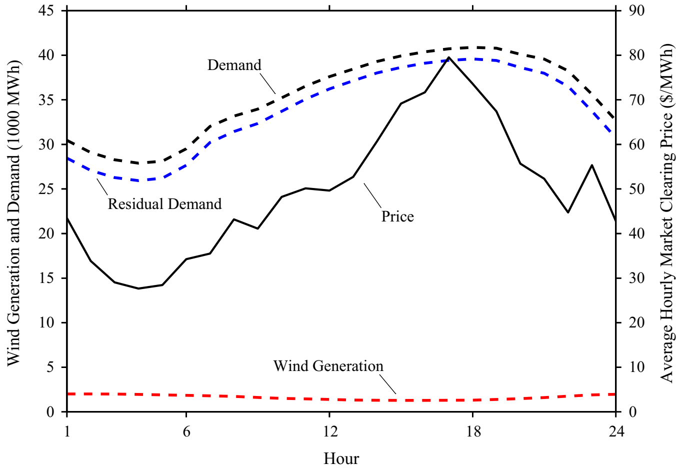

Fig. 2. Average hourly ERCOT residual demand and price.

early evening. The average levels of wind generation follow the opposite pattern—peaking at an average of 2008 MWh at 2 a.m. and falling to 1280 MWh at 3 p.m.

Compared to the aggregate demand, ERCOT wind generation levels are quite small. Over the three year period, hourly wind generation never exceeds 6000 MWh and during many hours, the aggregate level of wind generation falls all the way to 0 MWh. In contrast, hourly ERCOT demand never falls below 19 000 MWh. As a result, the average hourly residual demands, which are displayed in Fig. 2, follow the same pattern as hourly demand.

In addition to the residual demand, we use the hourly average wholesale electricity prices to identify the off-peak and peak periods. While the majority of electricity generated in the Texas market is purchased through bilateral contracts, a centralized balancing market is operated to balance the quantity of electricity supplied with the quantity demanded. Each day, Qualified Scheduling Entities (QSE), representing portfolios of electricity generators, submit balancing supply curves for each fifteen minute interval of the following day.[27] These balancing supply curves list the increase or decrease in generation each QSE will provide at different prices. To equate supply and demand, ERCOT purchases the necessary amount of up or down balancing energy at a single market clearing price.[28] Fig. 2 plots the average market clearing price by hour over the three year sample.[29] Following the pattern displayed by the residual demand, the minimum average price occurs during the 4 a.m. hour while the maximum average price occurs between 4 a.m. and 5 p.m.

5. Marginal emission rates

To predict the impact of arbitraging electricity between the off-peak and peak periods, we estimate the marginal emission rate in the Texas market at different points in time. We use a strategy similar to Callaway and Fowlie (2009) and Graff-Zivin et al. (2012) to first estimate average marginal emission rates by hour over the full three year sample.[30] To allow for seasonal variation, we next estimate the hourly marginal emission rates by month.

5.1. Average hourly marginal emission rates

The general specification we estimate is shown below:

$$E_{h,d} = \beta_h \cdot G_{h,d} + \alpha_{h,m} + \varepsilon_{h,d}, \tag{9}$$

where $h = 1, \ldots, 24$ represents the individual hours of each day $d = 1, \ldots, 1095$ and $\alpha_{h,m}$ is an hourly fixed affect that is allowed to vary across each of the 36 months in the sample. $E_{h,d}$ is the aggregate hourly emissions of CO_2 (tons), NO_X (lbs), or SO_2 (lbs). $G_{h,d}$ represents the hourly aggregate generation (MWh) from dispatchable sources. To calculate $G_{h,d}$, we sum the hourly net generation from coal, natural gas, nuclear, hydroelectric, and 'other' sources in the ERCOT market. Therefore, the coefficient β_h represents the average change in emissions caused by a change in dispatchable generation during hour h.

Three estimates of Eq. (9) are simultaneously made using CO_2, NO_X , and SO_2 as the dependent variables. To control for arbitrary serial correlation and heteroskedasticity, the errors are clustered at the daily level. Table 3 reports the estimates of

[27] These balancing supply bids can be adjusted up to one hour before real-time.

[28] If transmission limits between regions are binding, then four separate prices are set in each of the four ERCOT congestion zones (North, South, Houston, and West).

[29] If the market clearing price varies across congestion zones, a simple average of the four prices is taken.

[30] Siler-Evans et al. (2012) employ a similar reduced form strategy to estimate marginal emission rates. However, instead of estimating the marginal emission rates at different points in time, the authors estimate the marginal emission rates by levels of load.

Table 3
Average marginal emission rates by hour.

Hour	CO_2 tons/MWh		NO_X lbs/MWh		SO_2 lbs/MWh	
	β	Std. Err.	β	Std. Err.	β	Std. Err.
1	0.61*	(0.007)	0.62*	(0.02)	1.52*	(0.09)
2	0.62*	(0.007)	0.64*	(0.02)	1.80*	(0.09)
3	0.64*	(0.008)	0.66*	(0.02)	2.05*	(0.10)
4	0.65*	(0.008)	0.69*	(0.02)	2.15*	(0.10)
5	0.64*	(0.008)	0.69*	(0.02)	2.01*	(0.09)
6	0.63*	(0.008)	0.74*	(0.02)	1.81*	(0.09)
7	0.62*	(0.007)	0.72*	(0.02)	1.63*	(0.08)
8	0.60*	(0.007)	0.79*	(0.02)	1.36*	(0.08)
9	0.59*	(0.007)	0.62*	(0.02)	1.04*	(0.08)
10	0.57*	(0.007)	0.57*	(0.02)	0.78*	(0.08)
11	0.57*	(0.006)	0.56*	(0.02)	0.67*	(0.08)
12	0.57*	(0.006)	0.59*	(0.02)	0.65*	(0.08)
13	0.57*	(0.006)	0.66*	(0.02)	0.57*	(0.07)
14	0.57*	(0.005)	0.78*	(0.02)	0.53*	(0.06)
15	0.58*	(0.005)	0.91*	(0.02)	0.51*	(0.06)
16	0.58*	(0.005)	0.99*	(0.02)	0.51*	(0.06)
17	0.58*	(0.005)	1.03*	(0.03)	0.47*	(0.06)
18	0.57*	(0.005)	1.02*	(0.03)	0.41*	(0.06)
19	0.57*	(0.005)	0.92*	(0.02)	0.41*	(0.06)
20	0.56*	(0.005)	0.79*	(0.02)	0.46*	(0.06)
21	0.56*	(0.006)	0.71*	(0.02)	0.47*	(0.07)
22	0.56*	(0.006)	0.64*	(0.02)	0.59*	(0.07)
23	0.56*	(0.006)	0.61*	(0.02)	0.72*	(0.08)
24	0.59*	(0.006)	0.58*	(0.02)	1.08*	(0.08)
N	26 088		26 088		26 088	
R^2	0.98		0.90		0.62	

Models estimated simultaneously. Clustered standard errors in parentheses.

* Significant at the 1% level.

β_h for each pollutant. The point estimates are all positive and significant at the 1% level. An additional MWh of dispatchable generation during any hour will, on average, increase the hourly level of each of the three pollutants. The results also reveal that a marginal increase in generation will, on average, increase the aggregate emissions by different amounts during different hours. The first three panels of Fig. 3 plot the hourly estimates of $\hat{\beta}_h$, along with the corresponding 95% confidence intervals, for each of the three pollutants. Average marginal CO_2 and SO_2 rates peak between 3 a.m. and 4 a.m. and fall to their lowest levels between 6 p.m. and 7 p.m. In contrast, the average marginal NO_X rates peak at 5 p.m. and fall to their lowest average levels around 11 a.m. and midnight.

To examine what is driving the variation in the marginal emission rates, we estimate the following specification:

$$G_{j,h,d} = \beta_{j,h} \cdot G_{h,d} + \alpha_{h,m} + \varepsilon_{j,h,d} \tag{10}$$

where $G_{j,h,d}$ is the aggregate hourly generation from fuel source j={Low Heat-Rate Gas, High Heat-Rate Gas, Coal, Nuclear, Hydroelectric, 'Other'}. The coefficient of interest, $\beta_{j,h}$, represents fuel source j's average share of the marginal dispatchable generation during hour h. The bottom right panel of Fig. 3 plots the average hourly marginal generation by fuel source. The results demonstrate that the composition of the marginal dispatchable generation varies substantially across hours. On average, coal fired generation accounts for almost one-third of the marginal dispatchable output at 3 a.m. The average share of coal generation on the margin steadily falls to its lowest point between 5 p.m. and 6 p.m. Given that coal generation has the highest CO_2 and SO_2 intensities, these results explain why the average marginal CO_2 and SO_2 rates peak in the early morning and fall to their lowest points in the afternoon.

Fig. 3 also demonstrates that, on average, high heat-rate natural gas generation accounts for the largest share of the marginal output during 5 p.m. to 6 p.m. Recall from Table 2, these high heat-rate gas units tend to have the highest NO_X emission intensities. This explains why, on average, the marginal NO_X rate peaks in the early evening hours.

5.2. Marginal emission rates by month

The previous estimates represent the average marginal emission rates, for each hour, over the course of the entire sample. However, the marginal emission rate for a specific hour will likely change over the course of a year. Fig. 4 shows the average daily minimum and maximum residual demands, separated by month, on the Texas grid. The plot reveals large variations in the minimum and maximum daily residual demands across seasons. Therefore, the set of units on the margin

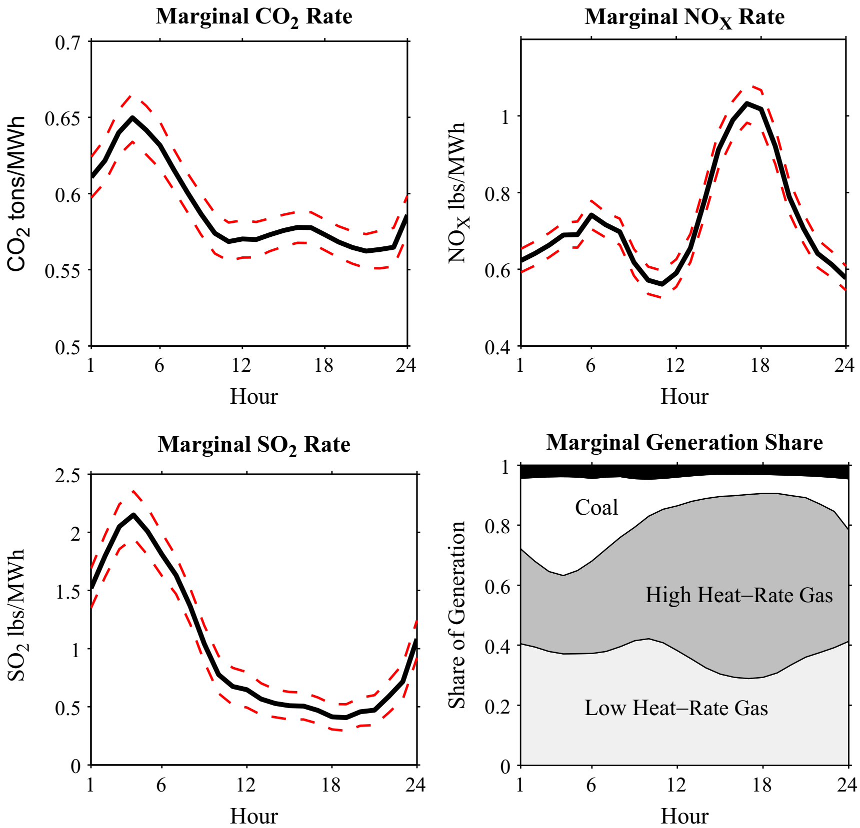

Fig. 3. Average hourly marginal emission rates and generation shares.

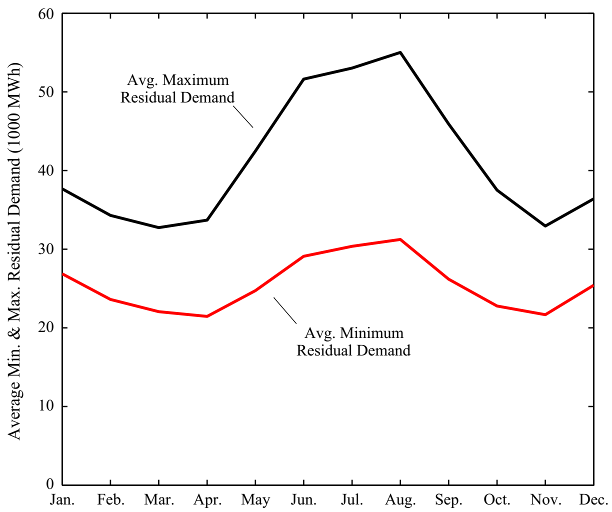

Fig. 4. Average daily minimum and maximum residual demand by month.

during the off-peak and peak hours, and thus the off-peak and peak marginal emission rates, will be different across months.[31]

[31] On top of the variation in the residual demand, the quantity of baseload nuclear output varies systematically across months. During the low demand spring and fall months, the nuclear units are often taken off-line for maintenance and re-fueling. Therefore, at the same level of residual demand, more fossil fuel generation will be dispatched during the spring and fall to replace the missing nuclear output.

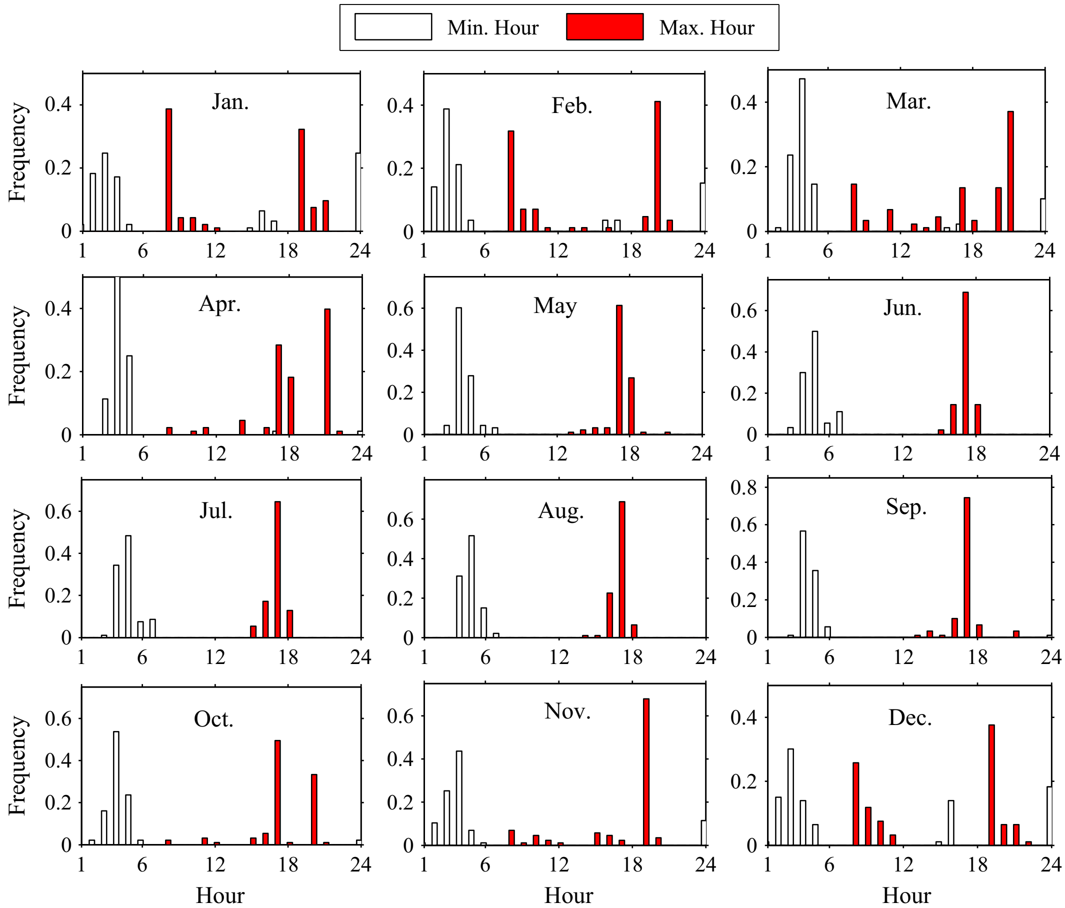

Fig. 5. Frequency distribution of minimum and maximum residual demand hours.

In addition, when the off-peak and peak hours occur also varies across the course of a year. For each day in the three year sample, we identify which hour had the lowest residual demand and which hour had the highest residual demand. Fig. 5 displays the frequency distributions of the minimum and maximum residual demand hours for each month. During May through November, the minimum residual demand hours are concentrated during the early morning hours (from 3 a.m. to 5 a.m.) and the maximum residual demand hours are concentrated during the late afternoon (from 5 p.m. to 7 p.m.). During December through April, the distribution of the minimum and maximum residual demand hours is more dispersed. In several of the months, the distribution of the minimum and maximum hourly residual demands is often bimodal. This is due to the fact that the daily demand profiles reach local maximums during the mid-morning and during the afternoons.

Combined, Figs. 4 and 5 demonstrate that the residual demand during the off-peak and peak hours, as well as the timing of the off-peak and the peak hours, will change across months. To accurately estimate the impact of arbitrage on aggregate emissions, separate estimates of the off-peak and peak marginal emission rates are needed for different months. To predict these values, we re-estimate Eq. (9), allowing the coefficients to vary across both hours and months. The specification is shown here:

$$E_{h,d} = \beta_{h,m} \cdot G_{h,d} + \alpha_{h,m} + \varepsilon_{h,d}, \tag{11}$$

The errors are again clustered across each individual day. The coefficient of interest, $\beta_{h,m}$, represents the average change in emissions from an additional MWh of dispatchable generation during hour h of month m.

The panels in Fig. 6 display the point estimates of average hourly marginal CO_2 rates, $\hat{\beta}_{h,m}$, for each month. The plots demonstrate that there is substantial variation in the marginal emission rates across the hours of a single day, as well as across the same hour in different months. During most of the months, the average hourly marginal CO_2 rate peaks in the early morning hours and falls to its lowest levels in the afternoon hours. During May for example, the average hourly marginal CO_2 rate peaks at a value of 0.77 tons of CO_2 per MWh at 5 a.m. and falls to around 0.58 tons of CO_2 per MWh during the late afternoon. Similar to the marginal CO_2 rates, the marginal SO_2 rates peak during the early morning hours and reach their lowest points during the afternoon.[32] Coal fired units are responsible for essentially all of the SO_2 emitted by the

[32] Corresponding plots of the marginal SO_2 rates are available from the authors upon request.

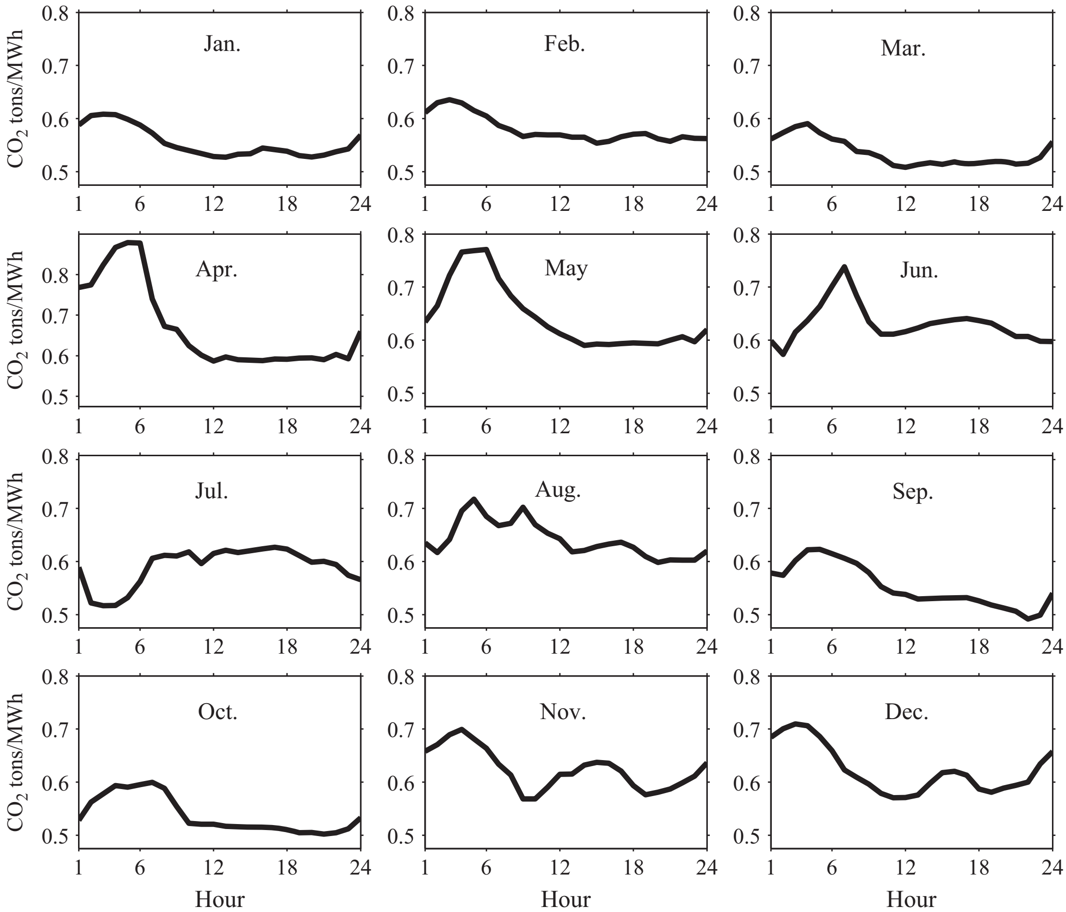

Fig. 6. Average hourly marginal CO_2 rates by month.

electric sector. Therefore, the variation in the marginal SO_2 rates is determined almost entirely by the variation in the share of coal generation on the margin.

Fig. 7 plots the average hourly NO_X marginal emission rates across each month. In contrast to the marginal CO_2 rates, the average marginal NO_X rates tend to peak during the afternoon. This stems from the fact that the highest private cost generators, the high-heat rate natural gas units, represent the largest share of the marginal generation during the peak demand hours of the afternoon. Given that these less efficient natural gas units have the highest NO_X emission intensities, the marginal NO_X rates peak during the afternoon. This fact is most pronounced during the high demand summer months of May through September.

6. Simulation

This section simulates the impact of a hypothetical electricity storage unit on the short-run emissions of CO_2, NO_X, and SO_2. Rather than modeling the dynamically optimized charging and discharging decisions of a profit maximizing storage owner, we assume that the storage unit demands electricity from the grid during the off-peak period and supplies the electricity in the subsequent peak period. We examine the impact of a storage unit which has a storage capacity of 1 MWh and can charge fully during a single hour.[33] While we focus on the case where a storage unit demands electricity over a single off-peak hour, extending the analysis to the case where a storage unit demands power over multiple off-peak hours is straightforward.[34] To explore the effect of different storage efficiencies, we allow the loss rate to vary.

[33] We estimate the change in daily emissions per MWh of off-peak electricity stored. Therefore, continuing to assume the storage unit is small relative to total demand, our results are directly applicable for estimating the impact of storage units with capacities larger than 1 MWh—the impact on emissions will be proportional to capacity.

[34] The empirical results demonstrate that, in general, the maximum difference between hourly marginal emission rates occurs between the highest and lowest residual demand hours. Therefore, by storing electricity over multiple off-peak hours, and then re-supplying the electricity over multiple peak hours, the difference between the off-peak marginal emission rates and peak marginal emission rates will decrease. However, the spread between the average prices during charging and discharging will also fall. Therefore, the external costs and private benefits will both decrease with charging duration.

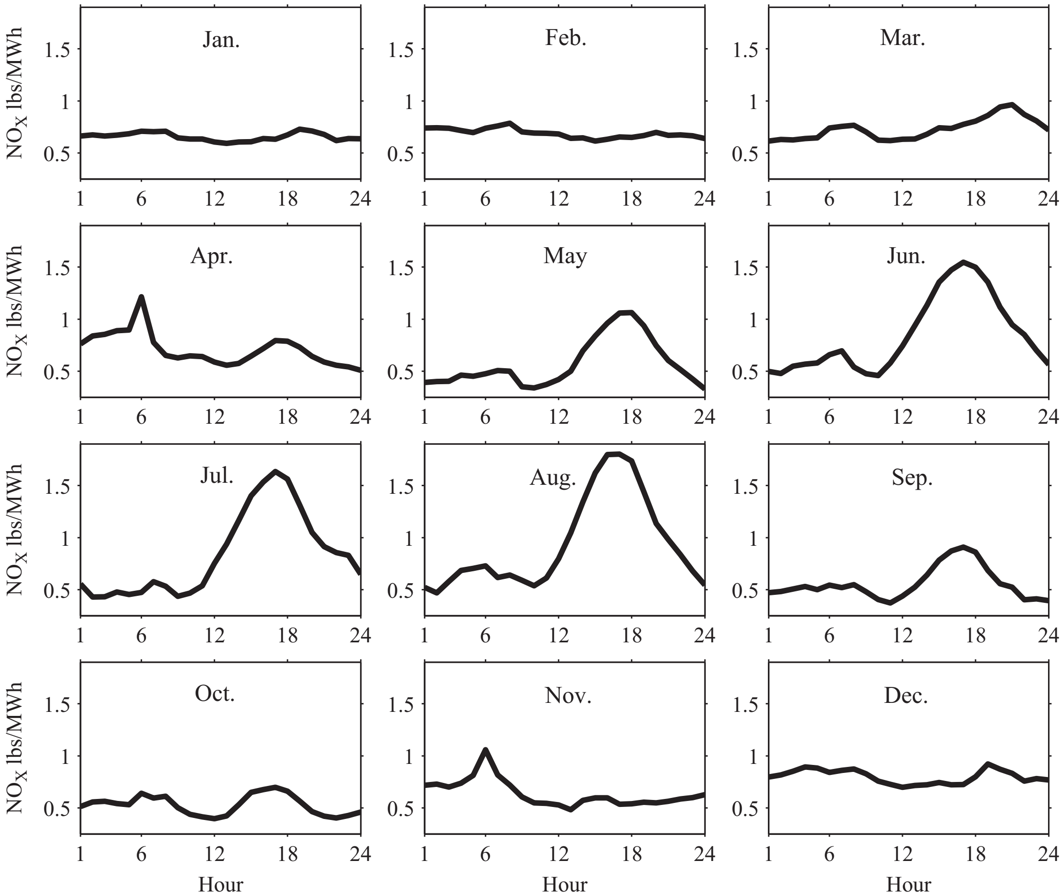

Fig. 7. Average hourly marginal NO_X rates by month.

6.1. Off-peak and peak marginal emission rates

To calculate the average off-peak and peak marginal emission rates, we weight the estimates of $\beta_{h,m}$ from Eq. (11) by the fraction of the time the off-peak period, or the peak period, occurs during hour h of month m. For example, assume during month m the daily peak hour occurred half the time at 5 p.m. ($h=17$) and at 6 p.m. ($h=18$) the other half. Our measure of the average peak marginal emission rate would be equal to $\hat{e}'_{p,m} = (\hat{\beta}_{17,m} + \hat{\beta}_{18,m})/2$.

To determine the distribution of the daily off-peak and peak hours, we use two different strategies. The first method uses the frequency distribution of the hours with the minimum and maximum daily residual demands displayed in Fig. 5. For month m, $\underline{f}_{h,m}$ represents the frequency the minimum daily residual demand occurs during hour h. Similarly, $\overline{f}_{h,m}$ represents the frequency the maximum daily residual demand occurs during hour h during month m. The second method uses the frequency distribution of the hours with the minimum and maximum daily market clearing prices. Both distributions are very similar, and as a result, produce very similar estimates of the monthly average off-peak and peak marginal emission rates.

To predict the off-peak and peak marginal emission rates for month m, we calculate the weighted average of the 24 hourly estimates of $\beta_{h,m}$. For each month, the off-peak and the peak marginal emission rates, $\hat{e}'_{o,m}$ and $\hat{e}'_{p,m}$, respectively, are given by

$$\hat{e}'_{o,m} = \sum_{h=1}^{24} \underline{f}_{h,m} \cdot \hat{\beta}_{h,m} \tag{12}$$

$$\hat{e}'_{p,m} = \sum_{h=1}^{24} \overline{f}_{h,m} \cdot \hat{\beta}_{h,m}. \tag{13}$$

The panels of Fig. 8 plot the average off-peak and peak marginal emission rates for each of the three pollutants. The solid lines represent the estimates made using the frequency distributions of the minimum and maximum residual demand hours. The dashed lines represent the estimates made using the frequency distributions of the minimum and maximum price hours.

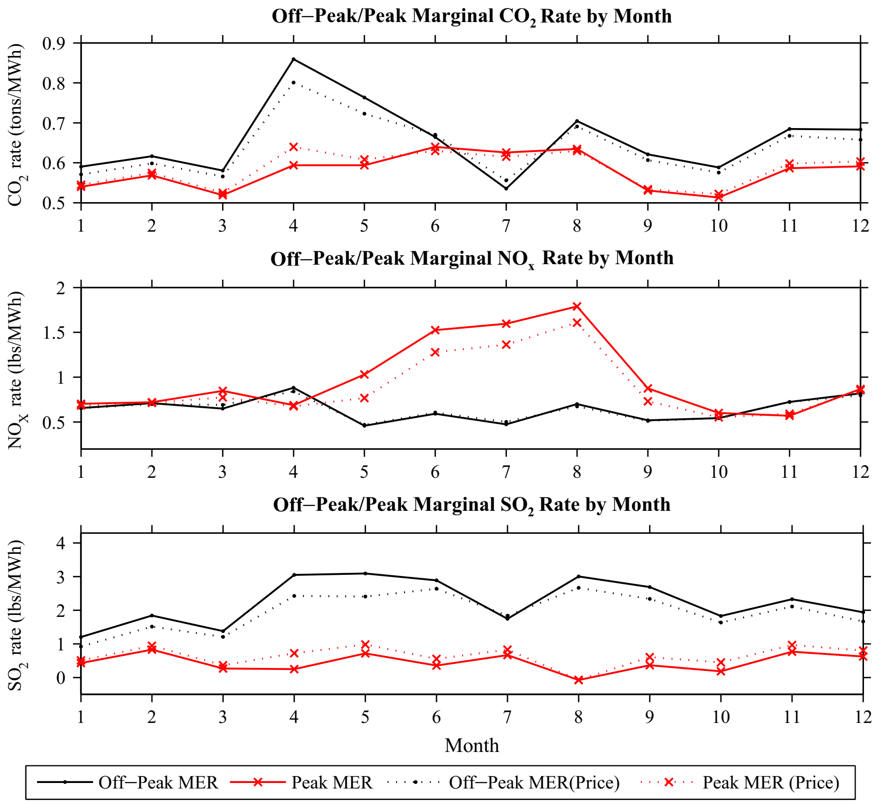

Fig. 8. Average off-peak and peak marginal emission rates by month.

The top panel reveals that, with the exception of July, the marginal off-peak CO_2 rates exceed the marginal peak CO_2 rates. During the spring and fall months (April, May/September, October, November), the off-peak marginal CO_2 rates are over 0.08 tons per MWh larger than the peak marginal CO_2 rates. These results are largely driven by the fact that coal generation accounts for a larger share of the off-peak marginal generation. During the peak demand summer months, the share of coal generation on the margin off-peak falls and the share of inefficient, high heat-rate gas units on the margin during the peak periods rise. As a result, the peak marginal CO_2 rate exceeds the off-peak marginal CO_2 rate during July.

In contrast to CO_2, Fig. 8 demonstrates that marginal NO_X rates are consistently higher during the peak hours. This is most pronounced between May and September when the peak demand tends to be quite large. Again, during these summer months, inefficient gas units, with high NO_X emission rates, account for a large share of the marginal peak generation.

Finally, Fig. 8 reveals that the off-peak marginal SO_2 rate exceeds the peak marginal SO_2 rate in each month. The off-peak and peak marginal SO_2 rates are primarily driven by the share of coal generation on the margin during the respective periods. Coal fired units, which have low marginal generation costs, typically operate at full capacity during the peak hours. As a result, the peak marginal SO_2 rate during the summer months is essentially zero.

6.2. *Impact of arbitrage on emissions*

This section uses the estimates of the average off-peak and peak marginal emission rates to examine the impact of electricity arbitrage on daily emissions. We simulate a hypothetical storage unit that stores a MWh of electricity during each off-peak period and supplies the stored energy during the subsequent peak period.

Recall from the analytical model, a marginal increase in arbitrage will result in the following change in emissions:

$$\frac{\partial e}{\partial s_o} = e'_o - (1-\alpha) \cdot e'_p, \tag{14}$$

where e is the daily aggregate emissions and α is the loss rate of the storage unit. We estimate the value of $\partial e/\partial s_o$ for a storage device with loss rates of $\alpha = \{0.3, 0.2, 0.1, 0\}$. PHS and CAES units in operation have loss factors typically between 0.1 and 0.3. Therefore, the hypothetical storage units modeled represent the current technology, as well as the impact of potentially more efficient, future storage technologies.

Table 4
Average Impact of arbitraging a MWh of electricity on aggregate daily emissions.

Month	CO_2 (tons/MWh)				NO_X (lbs/MWh)				SO_2 (lbs/MWh)			
	$\alpha=0.3$	$\alpha=0.2$	$\alpha=0.1$	$\alpha=0$	$\alpha=0.3$	$\alpha=0.2$	$\alpha=0.1$	$\alpha=0$	$\alpha=0.3$	$\alpha=0.2$	$\alpha=0.1$	$\alpha=0$
January	0.21**	0.16**	0.10**	0.05**	0.16**	0.09**	0.02	−0.05	0.90**	0.86**	0.82**	0.78**
February	0.22**	0.16**	0.10**	0.05**	0.21**	0.13**	0.06	−0.01	1.26**	1.18**	1.10**	1.02**
March	0.22**	0.17**	0.11**	0.06*	0.06	−0.03	−0.11	−0.20*	1.19**	1.16**	1.14**	1.11**
April	0.44**	0.38**	0.33**	0.27**	0.40**	0.33**	0.26**	0.19*	2.88**	2.85**	2.83**	2.80**
May	0.35**	0.29**	0.23**	0.17**	−0.26*	−0.37**	−0.47**	−0.57**	2.59**	2.52**	2.45**	2.38**
June	0.22**	0.15**	0.09**	0.02	−0.48**	−0.63**	−0.78**	−0.93**	2.64**	2.60**	2.57**	2.53**
July	0.10*	0.03	−0.03	−0.09*	−0.64**	−0.80**	−0.96**	−1.12**	1.28**	1.21**	1.15*	1.08*
August	0.26**	0.20**	0.13**	0.07	−0.55**	−0.73**	−0.91**	−1.09**	3.06**	3.07**	3.07**	3.08**
September	0.25**	0.20**	0.14**	0.09**	−0.09	−0.18**	−0.27**	−0.36**	2.44**	2.40**	2.36**	2.33**
October	0.23**	0.18**	0.13**	0.08**	0.12*	0.06	0.00	−0.06	1.70**	1.68**	1.66**	1.64**
November	0.27**	0.22**	0.16**	0.10**	0.33**	0.27**	0.21**	0.15*	1.79**	1.72**	1.64**	1.56**
December	0.27**	0.21**	0.15**	0.09**	0.21**	0.12**	0.04	−0.05	1.50**	1.44**	1.38**	1.31**
Average	0.25**	0.19**	0.14**	0.08**	−0.05*	−0.15**	−0.25**	−0.34**	1.94**	1.89**	1.85**	1.80**
(Std. Dev.)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.10)	(0.10)	(0.10)	(0.10)

Emission changes represent average change in daily emissions caused by arbitraging a MWh of off-peak electricity during a month. Loss rates of the hypothetical storage unit represented by α. Averages are equal to the annual weighted average of the impact on emissions.
* Significant at the 5% level.
** Significant at the 1% level.

To estimate the change in emissions, $\hat{e}'_m$, caused by storing 1 MWh of off-peak electricity during month m, we calculate the following value:

$$\hat{e}'_m = \hat{e}'_{o,m} - (1-\alpha)\hat{e}'_{p,m} = \sum_{h=1}^{24} [\underline{f}_{h,m} - (1-\alpha)\overline{f}_{h,m}] \cdot \hat{\beta}_{h,m}, \tag{15}$$

where $\underline{f}_{h,m}$ and $\overline{f}_{h,m}$ are the weights from the frequency distributions of the minimum and maximum residual demand hours, respectively. The estimates of the hourly marginal emission rates from Eq. (11) are used for $\hat{\beta}_{h,m}$. To calculate the standard deviation of the point estimates of $\hat{e}'_m$, we treat the weights from the residual demand distributions as known constants. Therefore, the estimates of the average change in emissions caused by storing a MWh of off-peak electricity are simple linear combinations of the estimates of the hourly marginal emission rates.

Table 4 presents the estimates of the impact arbitraging a MWh of off-peak electricity will have on the daily level of CO_2, NO_X , and SO_2 emitted. Consistent with the results presented in Fig. 8, arbitraging electricity will generally increase the daily emissions of CO_2. The only exception is during July when the peak marginal CO_2 rate exceeds the off-peak marginal emission rate. Even during July, a storage unit will need to have a loss rate near $\alpha=0$ in order to achieve any emission reductions. With a loss rate of 0.3, storing off-peak electricity, and re-supplying the energy during the daily peak hour, will increase the daily CO_2 by an average of 0.25 tons per MWh stored. To put this estimate into perspective, we compare the CO_2 created by arbitraging electricity to the emissions created by burning gasoline. An automobile produces 17.68 pounds of CO_2 per gallon of gasoline consumed.[35] Therefore, arbitraging 1 MWh of ERCOT electricity each day for a single year will increase aggregate CO_2 emissions by the same amount as burning 10 322 gallons of gasoline.

Like CO_2, arbitraging electricity will uniformly increase predicted daily emissions of SO_2. In most cases, increasing the efficiency of the hypothetical storage unit does not substantially alter the estimated impact on SO_2. This is because the peak marginal SO_2 rates tend to be quite small. Therefore, even if none of the energy is lost during the storage process, the quantity of SO_2 being offset during the peak period is trivial compared to the increase in off-peak SO_2 emissions.[36]

In contrast to CO_2 and SO_2, the results in Table 4 demonstrate that, on an average, NO_X emissions will fall when electricity is arbitraged across periods. The predicted reductions in NO_X are the largest during the summer months when the peak marginal NO_X rates are the greatest. In contrast to the predicted impact on SO_2, increasing the efficiency of the storage unit has large impacts on the quantity of NO_X avoided. This is because the peak marginal NO_X rates become quite large in the high demand months.

6.3. External and private benefits of arbitrage

The two-period model presented in Section 2 demonstrates that the marginal private benefit and the marginal social benefit of electricity arbitrage can differ if the wholesale prices do not accurately reflect the social cost of pollution.

[35] The emission intensity of gasoline is provided by the U.S. Energy Information Administration (EIA). The estimate of 17.68 pounds of CO_2 per gallon assumes the gasoline has 10% ethanol. See the EIA site for more information; http://www.eia.gov/oiaf/1605/coefficients.html#tbl2.

[36] Although the point estimate is not statistically different than zero, during August, the estimate of the peak marginal SO_2 rate is slightly negative. As a result, increasing the efficiency of the storage unit results in a slight increase in the predicted level of SO_2 emissions.

Table 5
Average external and private benefits of arbitraging a MWh of electricity.

Month	External benefit (CO_2=$21/ton)				External benefit (CO_2=$65/ton)				Private benefit			
	$\alpha=0.3$	$\alpha=0.2$	$\alpha=0.1$	$\alpha=0$	$\alpha=0.3$	$\alpha=0.2$	$\alpha=0.1$	$\alpha=0$	$\alpha=0.3$	$\alpha=0.2$	$\alpha=0.1$	$\alpha=0$
January	−4.45**	−3.32**	−2.18**	−1.05**	−13.78**	−10.27**	−6.76**	−3.25**	4.89**	11.04**	17.18**	23.32**
February	−4.59**	−3.39**	−2.20**	−1.00**	−14.20**	−10.50**	−6.80**	−3.11**	8.19**	13.94**	19.69**	25.44**
March	−4.56**	−3.47**	−2.38**	−1.29*	−14.12**	−10.75**	−7.37**	−4.00*	4.81**	10.23**	15.65**	21.07**
April	−9.32**	−8.07**	−6.83**	−5.58**	−28.85**	−24.99**	−21.13**	−17.27**	16.98**	23.59**	30.20**	36.81**
May	−7.30**	−6.05**	−4.81**	−3.56**	−22.60**	−18.74**	−14.88**	−11.02**	24.88**	32.59**	40.31**	48.02**
June	−4.55**	−3.20**	−1.86**	−0.52	−14.08**	−9.92**	−5.76**	−1.60	25.67**	34.31**	42.95**	51.59**
July	−2.05*	−0.73	0.58	1.89*	−6.34*	−2.27	1.80	5.86*	34.69**	43.88**	53.07**	62.26**
August	−5.47**	−4.13**	−2.80**	−1.47	−16.92**	−12.79**	−8.67**	−4.54	38.50**	48.46**	58.42**	68.38**
September	−5.24**	−4.13**	−3.01**	−1.90**	−16.22**	−12.78**	−9.33**	−5.88**	35.58**	43.56**	51.53**	59.51**
October	−4.81**	−3.74**	−2.66**	−1.58**	−14.90**	−11.56**	−8.23**	−4.89**	23.23**	29.52**	35.81**	42.10**
November	−5.75**	−4.52**	−3.29**	−2.06**	−17.81**	−14.00**	−10.19**	−6.38**	20.76**	26.93**	33.11**	39.29**
December	−5.66**	−4.41**	−3.17**	−1.93**	−17.50**	−13.66**	−9.82**	−5.98**	10.17**	16.46**	22.75**	29.04**
Average	−5.31**	−4.09**	−2.88**	−1.67**	−16.43*	−12.67**	−8.92**	−5.16**	20.75**	27.94**	35.13**	42.32**
(Std. Dev.)	(0.18)	(0.18)	(0.18)	(0.19)	(0.56)	(0.56)	(0.57)	(0.58)	(1.89)	(2.16)	(2.43)	(2.71)

Loss rate of storage unit represented by α. Monthly average external benefit is equal to the product of the average change in CO_2 per MWh stored and the external cost of CO_2. Private benefit calculated by multiplying the average peak prices across each month by $(1-\alpha)$ and subtracting the average off-peak price. Averages are equal to the annual weighted average private and external benefits per MWh stored (standard deviations in parentheses).

* Significant at the 5% level.

** Significant at the 1% level.

This section examines the extent to which the marginal private and marginal social benefits of electricity arbitrage differ in the Texas electricity market. Combining the estimates of the average impact on emissions with information on the average off-peak and peak wholesale electricity prices, we demonstrate that the marginal private benefits of arbitrage exceed the marginal social benefits by a sizable amount.

The results in Table 4 show that electricity arbitrage will affect the short-run level of pollution emitted. In the Texas market, the daily aggregate emissions of CO_2 and SO_2 will increase with arbitrage while the quantity of NO_X will generally decrease. CO_2 emissions are not subject to any form of regulation; therefore, short-run increases in the emissions of CO_2 represent real increases in the aggregate level of pollution.

In contrast to CO_2, the emissions of SO_2 and NO_X are subject to national and regional caps. Over the three years examined, national emissions of SO_2 are capped by the Acid Rain Program. In addition, beginning in 2009, the EPA's Clean Air Interstate Rule (CAIR) places a cap on the aggregate annual NO_X emissions from Texas and many eastern states.[37] As a result, short-run changes in SO_2 or NO_X emissions will not represent long-run changes in the aggregate level of pollution. Instead, changes in the short-run level of SO_2 and NO_X will result in an increase or decrease in the number of permits that can be used to pollute at a different time or in a different location.

Despite the fact that the aggregate level of SO_2 and NO_X emissions will not change over the long-run with increased arbitrage, the social cost of these emissions can change. Unlike CO_2, both SO_2 and NO_X are not perfectly mixing pollutants. Where and when the emissions occur can alter the social costs. For example, arbitrage may reduce the level of NO_X from natural gas units located near population centers. If the freed up NO_X permits are used by fossil fuel units located farther from demand centers, the social cost of the pollution may in fact be reduced. Additionally, if the non-perfectly mixing pollution occurs during the off-peak, nighttime hours instead of the peak daytime hours, the costs incurred may differ.[38]

In this study, we focus on the impact of arbitrage on the external costs of the unregulated CO_2 emissions. To determine the external costs from changes in the quantity of CO_2 emitted, we use values for the social cost of carbon from the IAWG (2010) report. The report provides a central estimate of $21/ton for the external cost of CO_2 as well as a high cost estimate of $65/ton of CO_2.

Table 5 presents the estimates of the average external benefit, by month, of arbitraging 1 MWh of off-peak electricity for different levels of α. Given that arbitrage will generally increase the daily emissions of CO_2, the external benefits are consistently negative. As the storage unit becomes more efficient, the average external benefit becomes less negative. Using the high estimate of the social cost of CO_2, the average external costs of arbitrage are substantially larger.

[37] Starting in 2010, after the years examined in this study, annual SO_2 emissions are also capped in the states covered by the CAIR. In addition, the CAIR program places a cap on ozone season NO_X emissions in several states. However, Texas is only regulated under the annual SO_2 and NO_X caps. Finally, annual NO_X emissions from generators located specifically in the Houston–Galveston–Brazoria ozone nonattainment area are also capped by the Mass Emissions Cap and Trade Program (MECTP).

[38] Gilmore et al. (2010) simulate the impact of embedding utility-scale batteries in New York on the dispersion and resulting costs of locally mixing pollutants.

Recall from the two-period model, the marginal private returns to arbitrage are given by $(1-\alpha)\cdot P_p - P_o$, where P_p and P_o are the peak and off-peak wholesale electricity prices, respectively. To predict the private benefits of electricity arbitrage, we estimate the average monthly off-peak and peak electricity prices. For each month, we first calculate the average price during hour $h = 1, \ldots, 24$. We then estimate the average off-peak and peak prices by multiplying the hourly average prices by the corresponding weights of the minimum and maximum residual demand hours presented in Fig. 5.

Table 5 presents the estimates of the marginal profit a storage owner will earn by arbitraging 1 MWh of electricity between off-peak and peak hours each day.[39] The results demonstrate that, depending on the efficiency of the storage unit, the owner will earn between \$20.70 and \$42.24 per MWh of off-peak electricity stored. The largest monthly profits occur during the peak demand summer months when the peak wholesale prices on average exceed \$100/MWh.

The marginal social benefit of storage is equal to the sum of the marginal external benefit and the marginal private benefit. For each value of α, and for each value of the social cost of CO_2, the annual average marginal social benefit of storing a MWh of off-peak electricity falls below the marginal private benefit. Even with a perfectly efficient storage unit ($\alpha = 0$), the marginal private benefit exceeds the marginal social benefit of arbitrage during eleven of the twelve months. In the case where $\alpha = 0.3$, and the marginal social cost of CO_2 is \$65/ton, the external cost of arbitraging 1 MWh of off-peak electricity is larger than the average private benefit during five of the twelve months. While electricity arbitrage will earn positive profits for the storage owner during these months, the social benefit is actually below zero.

6.4. Discussion

Our results demonstrate that arbitrage will decrease the average daily emissions of NO_X and increase the average daily emissions of CO_2 and SO_2 in Texas. While our empirical strategy and the motivation for our analysis differs from Holland and Mansur's (2008) examination of the emissions impacts of reducing demand variability with real time pricing, we can compare the predictions presented in that study to our point estimates of the impact on arbitrage on emissions. The estimates from Holland and Mansur's parametric specification demonstrate that, on average, a 1% reduction in the coefficient of variation in the daily ERCOT demand increases daily CO_2 and SO_2 emissions by 0.9% and 3.6%, respectively. In contrast, a 1% reduction in the coefficient of variation in the daily demand reduces daily NO_X emission by 0.8%.[40]

To compare Holland and Mansur's results to our estimates of the average change in emissions caused by arbitrage, we first calculate the percentage change in the coefficient of variation in daily dispatchable generation caused by a hypothetical storage unit with a loss rate of $\alpha = 0.2$. To calculate the percentage change in the coefficient of variation of the daily dispatchable generation, we add 1 MWh of generation during each off-peak hour – defined as the hour with the minimum residual demand – and subtract $1-\alpha$ MWh from the peak residual demand hour of each day. Using this strategy, we find that a 1 MW storage unit will reduce the coefficient of variation in the daily dispatchable generation by −0.00084% over the period from 2007–2009.

Combining Holland and Mansur's elasticity estimates with the reduction in the coefficient of variation in daily dispatchable generation caused by arbitrage, we calculate the absolute increase, or decrease, in daily emissions caused by storing 1 MWh of off-peak electricity each day.[41] The results reveal that on an average, daily CO_2 will increase by 0.18 tons per MWh stored, daily NO_X will fall by 0.18 pounds per MWh stored, and daily SO_2 will increase by 2.82 pounds per MWh stored. Recall from Table 4, we find that on an average, storing 1 MWh of off-peak electricity with a storage unit that has a loss rate of $\alpha = 0.2$ will increase daily CO_2 emissions by 0.19 tons, reduce daily NO_X emissions by 0.15 pounds, and increase SO_2 emissions by 1.89 pounds.

The similarity between our estimates of the average impact of arbitrage in ERCOT and the predictions made using Holland and Mansur's results provides very strong support to the conclusions presented in this study. Recall that our empirical analysis focuses on the Texas market due to the fact that the regional grid is very isolated. Therefore, we do not need to be concerned about the impact of arbitrage on electricity flows between surrounding markets. Abstracting from the impact of daily demand variation on regional trading, Holland and Mansur's analysis covers the entire contiguous U.S. Their results suggest that the findings presented in our analysis are not unique to ERCOT. Holland and Mansur predict that decreasing the variation in daily generation will increase CO_2 emissions in over half of the regions examined. Compared to the ERCOT region, the authors estimate that the increase in daily CO_2 will be 267% larger in the Western Interconnection—the region which provides electricity to California. This result suggests that California's Energy Storage Portfolio, which mandates investment in storage capacity, will likely lead to sizable increases in aggregate CO_2 emissions.

[39] Given that we do not simulate the dynamically optimized charge and discharge decisions of a profit maximizing storage owner, these values can be thought of as representing reasonable lower bounds on the private returns to arbitrage. A storage owner that strategically strays from the simple rule being simulated – for example, by not arbitraging electricity during the weekends – may achieve a higher profit per MWh. However, given that the marginal CO_2 rates are consistently larger during the hours with low prices – due to the fact that coal units are more heavily on the margin – deviations from the simple simulation rule will likely have only small impacts on the estimates of the external costs of arbitrage.

[40] The parametric estimates of the impact of the within-day coefficient of variation on daily emissions are presented in Table 4.

[41] The estimates of the emission changes are relative to the average daily ERCOT emissions. Over the three year period we examine, the average daily ERCOT emissions equal 557 956 tons of CO_2, 626 583 pounds of NO_X , and 2 237 383 pounds of SO_2.

7. Conclusion

States have begun implementing policies which will spur dramatic increases in electricity storage capacity. These efforts are motivated largely by the belief that storage will play a vital role in integrating vast quantities of intermittent renewables. However, most regions currently have very small levels of intermittent renewable generation. Given the limited penetrations of renewable capacity, low cost renewables are generally not the marginal sources of electricity. As a result, arbitraging electricity across time will not alter the short-run level of renewable generation.

Instead, arbitrage will lead to increased off-peak conventional generation and decreased peak conventional generation. If the emission rates of the units on the margin during the peak periods are not sufficiently below the emission rates of the units on the margin during the off-peak periods, then arbitraging electricity will lead to increases in the short-run level of pollution. Focusing on the Texas electricity market, we demonstrate that arbitraging electricity will in fact lead to increases in unregulated emissions. For plausible estimates of the marginal external cost of pollution, our results demonstrate that during most of the year, the external costs incurred by arbitraging electricity actually outweigh the private benefits.

While storage capacity may provide sizable benefits in the future, at the current levels of renewable generation, bulk storage will likely increase unregulated emissions in many regions. If jump-starting investment in storage capacity leads to substantial learning and technological improvements, then these short-run emission increases may be justified. However, if the benefits provided by learning are small relative to the external costs of the increased pollution, then subsidies and requirements to expand storage capacity should be delayed until intermittent renewable capacity has grown substantially.

References

Abbey, Chad, Joos, Geza, 2007. Supercapacitor energy storage for wind energy applications. IEEE Transactions on Industry Applications 43 (3), 769–776.
Black, Mary, Strbac, Goran, 2007. Value of bulk energy storage for managing wind power fluctuations. IEEE Transactions on Energy Conversion 22 (1), 197–205.
Duncan, Callaway, Fowlie, Meredith, Greenhouse gas emissions reductions from wind energy: location, location, location? http://www.aere.org/meetings/documents/FOWLIE.pdf, 2009.
Cavallo, Alfred J., 1995. High-capacity factor wind energy systems. Journal of Solar Energy Engineering 117 (2), 137–143.
DeCarolis, Joseph F., Keith, David W., 2006. The economics of large-scale wind power in a carbon constrained world. Energy Policy 34 (4), 395–410.
Denholm, Paul, Kulcinski, Gerald L., 2004. Life cycle energy requirements and greenhouse gas emissions from large scale energy storage systems. Energy Conversion and Management 45 (13), 2153–2172.
Denholm, Paul, Sioshansi, Ramteen, 2009. The value of compressed air energy storage with wind in transmission-constrained electric power systems. Energy Policy 37 (8), 3149–3158.
Denholm, Paul, Holloway, Tracey, 2005. Improved accounting of emissions from utility energy storage system operation. Environmental Science & Technology 39 (23), 9016–9022.
Denholm, Paul, Ela, Erik, Kirby, Brendan, Milligan, Michael. The role of energy storage with renewable electricity generation, National Renewable Energy Laboratory, Technical Report 6A2-47187, 2010.
Dunn, Bruce, Kamath, Haresh, Tarascon, Jean-Marie, 2011. Electrical energy storage for the grid: a battery of choices. Science 334 (6058), 928–935.
Gilmore, Elisabeth, Apt, Jay, Walawalkar, Rahul, Adams, Peter, Lave, Lester, 2010. The air quality and human health effects of integrating utility-scale batteries into the New York State electricity grid. Journal of Power Sources 195 (8), 2405–2413.
Graff-Zivin, Joshua, Kotchen, Matthew J., Mansur, Erin T. Spatial and Temporal Heterogeneity of Marginal Emissions: Implications for Electric Cars and Other Electricity-Shifting Policies. UC Center for Energy and Environmental Economics Working Paper, 2012.
Graves, Frank, Jenkin, Thomas, Murphy, Dean, 1999. Opportunities for electricity storage in deregulating markets. The Electricity Journal 12 (8), 46–56.
Greenblatt, Jeffrey, Succar, Samir, Denkenberger, David, Williams, Robert, Soccolow, Robert, 2007. Baseload wind energy: modeling the competition between gas turbines and compressed air energy storage for supplemental generation. Energy Policy 35 (3), 1474–1492.
Hitaj, Claudia, 2013. Wind power development in the United States. Journal of Environmental Economics and Management 65 (3), 394–410.
Holland, Stephen, Mansur, Erin, 2008. Is real-time pricing green? The environmental impacts of electricity demand variance. Review of Economics and Statistics 90 (3), 550–561.
IAWG, Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866, Interagency Working Group on Social Cost of Carbon, 2010.
Mears, Dan, Gotschall, Harold, Key, Tom, Kamath, Haresh. EPRI-DOE Handbook of Energy Storage for Transmission and Distribution Applications, Electric Power Research Institute and the U.S. Department of Energy, 2003.
Rastler, Dan. Electricity Energy Storage Technology Options: A White Paper Primer on Applications, Costs and Benefits. Electric Power Research Institute, 2010.
Siler-Evans, Kyle, Azevedo, Ines, Morgan, M.G., 2008. Marginal emissions factors for the US electricity system. Environmental Science & Technology 46 (9), 4742–4748.
Sioshansi, Ramteen, 2011. Emissions impacts of wind and energy storage in a market environment. Environmental Science & Technology 45 (2), 10728–10735.
Sioshansi, Ramteen, Denholm, Paul, 2010. The value of plug-in hybrid electric vehicles as grid resources. The Energy Journal 31 (3), 1–23.
Sioshansi, Ramteen, Denholm, Paul, Jenkin, Thomas, Weiss, Jurgen, 2009. Estimating the value of electricity storage in PJM: arbitrage and some welfare effects. Energy Economics 31 (2), 269–277.
Succar, Samir, Williams, Robert H. Compressed air energy storage: theory, resources, and applications for wind power, Princeton Environmental Institute Report, 2008.
Swider, Derk J., 2007. Supercapacitor energy storage for wind energy applications. IEEE Transactions on Energy Conversion 22 (1), 95–102.
Swift-Hook, Donald T., 2010. Grid-connected intermittent renewables are the last to be stored. Renewable Energy 35 (9), 1967–1969.
Tuohy, Aidan, O'Malley, Mark. Impact of pumped storage on power systems with increasing wind penetration, Power & Energy Society General Meeting, 2009 (PES'09). IEEE, 2009, pp. 1–8.
Walawalkar, Rahul, Apt, Jay, Mancini, Rick, 2007. Economics of electric energy storage for energy arbitrage and regulation in New York. Energy Policy 35 (4), 2558–2568.