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Abstract[1]

This paper estimates the impact of solar and wind power intermittency on wholesale prices, arbitrage opportunities and the profitability of storage. First, I use the short term randomness of wind and solar generation to estimate the hourly reductions in wholesale electricity market prices (merit-order effect) in Mexico. Second, since hydropower is already acting as battery storage by smoothing the hourly intermittency of wind and solar, I use lags to control for the reallocation, to estimate the appropriate dynamic merit-order effect and to project future wholesale prices for larger renewables capacities. Third, I use dynamic optimization to assess the profitability of energy arbitrage for a marginal storer. Storage profits based on market average wholesale prices for 2019 (10.6 GW of wind and solar) are lower than the levelized cost of batteries (LCOE). For the 2029 planned wind and solar capacities (30.9 GW), storage arbitrage profits would be within the range of its projected declining LCOE for a 4-hour battery. Nevertheless, for nodes with large price variances and not fully transmission congested, arbitrage storage would be within the range of the LCOE sooner by 2025 (25.4 GW). Pumped-storage hydro arbitrages power at a lower rate which make its profits lower than those of the batteries. The full value of storage can be larger if we consider other services (e.g. frequency regulation). Similar lessons will apply to grids/countries with increasing shares of renewables and non-dominant hydropower.

JEL classifications: L94, Q41, Q42, Q47
Keywords: Wind and Solar Power, Storage, Hydropower, Merit-order effect

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1. Introduction

Wind and solar power are key technologies for abating air pollution and mitigating climate change in the developed and developing world. In the past two years, Mexico has significantly increased the capacity of both and the government plans to serve around 21 percent of electricity demand with intermittent renewables by 2025 (SENER, 2019). Battery storage will play a major role in the scale-up of intermittent solar and wind output by storing excess power and smoothing their daily cycles to serve peak demand. While the levelized cost of storage will decrease in the years ahead, its value should increase as intermittency intensifies with the installation of more solar and wind.

Previous energy economics research on storage assessed the profits for a marginal storer under current renewable energy capacities (Giuletti et al., 2018). Also, previous papers model the average merit-order effect of renewables on wholesale prices (Hirth, 2013), and more recent work analyzes the hourly heterogenous impact of solar and wind on prices (Bushnell and Novan, 2018). The main contribution of my work is to model the hourly merit-order effects of solar and wind on wholesale prices in Mexico while explicitly controlling for the dynamics of hydropower reallocation. Then, using the reduced form econometrics estimates, I project future hourly prices for the government planned wind and solar capacities (2025-2030) and assess the profitability of 1-hour, 4-hour and pumped-storage hydro (10-hour) marginal storers. I analyze storage profits based on average wholesale electricity prices (>2,000 nodes) and at specific high congestion and price variance nodes.

I use the short-term exogeneity of wind and solar generation to identify the hourly impacts of solar and wind power (marginal merit-order effect) on electricity prices in Mexico using 2018 to 2019 data. I propose a static and a dynamic specification which controls for hydropower reallocation. On average, the static model shows that wind power reduces wholesale prices during all hours of the day while solar power reduces them during daylight but increases prices at sunset, due to the additional costs of scheduling and using flexible gas generation to adjust to uncertain supply.

Hydropower already acts as storage by smoothing the hourly intermittency of wind and solar and reallocating generation from the hours with the largest renewable output to those with the lowest. After controlling for this effect with lags, the dynamic estimates show the shifted hydro completely offset the sunset price increase in 2019. Wind power price reductions decreased since the shifted hydro from hours with large wind generation appears to be directed to reduce the sunset

price hikes. The combined net effect of wind and solar generation during the day decreased daylight prices and flattened the price curve from 2018 to 2019. Using the conservative 95 percent confidence interval lower bound price impacts estimates, I project that morning prices will further decrease, creating more arbitrage opportunities as renewables expand.

The marginal storer profitability for energy arbitrage, evaluated at 2019 average wholesale prices and renewables capacities (5.9 GW for wind, 4.7 GW for solar), is lower than the levelized cost of batteries for all technologies: 1-hour, 4-hour batteries and pumped hydro. Under thrice the current solar and wind capacities in 2029 (14.7 GW for wind and 16.2 GW for solar), storage arbitrage profits are within its projected levelized cost (LCOE) for the 4-hour battery. At those nodes with high price variance but not fully congested, profits can be within the LCOE range by 2025 with the double of current capacities (25.4 GW for wind and solar combined). On the other hand, the node with the largest price variance is almost fully congested and the impact of renewables on its prices is smaller than for the average wholesale price, which makes its profits not within the LCOE range by 2025. Therefore, transmission and storage have complementarities and trade-offs which deserve appropriate assessment to deliver a cost-effective and clean power grid.

The 4-hour battery is likely to be the more profitable storage technology based on hourly power arbitrage since it can be located at those nodes with larger price variance, and due to its decreasing costs. Pumped-storage hydropower arbitrages power at a lower rate than the batteries, it is a mature technology with no fast declining costs, and it will be restricted to feasible sites. Hence, its profits will be within the range of its LCOE by 2030 (15.9 GW of wind and 17.5 GW of solar). Assessing storage profits for a two-day-horizon (interday arbitrage) does not significantly alter the profits except for pumped-hydro, which has a 5 percent boost. Thus, intraday arbitrage will very likely be the dominant business strategy in the nascent stages of the industry.

While the declining merit-order effect under larger renewables capacities and the larger hydropower smoothing of future planned reservoir plants make the storage arbitrage profits an upper bound, not adding the value of other services (e.g., frequency regulation) make these projections a conservative appraisal on the full profitability of the first pioneer storers. While the exact values and estimates of this paper would not hold in different contexts; the insights regarding the intermittency, price volatility and arbitrage opportunities increasing with the expansion of renewables, the role of hydropower in smoothing renewables fluctuations, and the pioneer

profitability of batteries at high volatility nodes can apply to other countries with increasing shares of renewables and non-dominant hydropower (e.g., Argentina, Chile).

Finally, I summarize the hourly (dis)charging actions of the battery for an entire year by clustering similar strategies with the Mixture of Gaussians Unsupervised Machine Learning algorithm. The clusters of charging strategies show that for current prices most patterns charge during the first hours of the day (3-7) to serve the evening peak demand (19-22); and for future prices, larger intermittency leads to charging and discharging continuously throughout all day.

This paper is organized as follows: Section 2 presents the literature review on merit-order effect estimation and storage value and profits. Section 3 displays data and the main trends on electricity demand, supply, renewable generation and prices in Mexico. Section 4 presents the econometric specifications to estimate the hourly static and dynamic merit-order effects of wind and solar, and to project future prices. Section 5 describes the dynamic optimization model to assess the profitability of energy arbitrage. Section 6 presents the merit-order effect regression estimates and price projections, and then it discusses the results on the profitability of storage and charging strategies. Section 7 discusses the results in light of the previous literature and limiting assumptions and finally Section 8 concludes.

2. Literature Review

Several studies in the energy economics literature have assessed the merit-order effect, which refers to reductions in wholesale electricity market prices due to the incoming zero fuel-cost wind and solar power. Hirth (2013), Würzburg et al. (2013) and Bushnell and Novan (2018) provide a good overview of these studies and classify them in simulation-based and empirical. The latter refers to the use of econometrics on ex post data to infer the impact of renewable energy on prices. Most studies focus on and report the average reduction in prices from adding one energy unit of renewable generation (MWh or GWh).

The main identification argument relies on the exogenous natural cycles of wind and solar generation. This premise has also been used to estimate the impacts of solar and wind power on carbon and air pollution emissions (Cullen, 2013). Furthermore, using instrumental variables, Novan (2015) and Castro (2019) find that the exogeneity assumption of renewable energy generation is plausible.

While the average reduction in prices is key for understanding and measuring the average market value of renewable energy, solar and wind power have daily cycles which determine heterogenous hourly output and impacts. Graff Zivin et al. (2014) and Holland et al. (2016) recognize this hourly heterogeneity in the marginal plant serving the load. They model the increase in carbon and air pollution emissions when charging electric vehicles by capturing the hourly marginal emissions of the power grid with a linear regression in which the exogenous load is interacted with indicator functions for each hour.

Bushnell and Novan (2018) extend this identification and modelling approach to capture the hourly merit-order effects of wind and solar in the California Independent System Operator (CAISO) from 2013 to 2017. The authors find that solar power decreased daylight wholesale electricity prices but increased those during non-daylight hours. This occurred since the flexible but expensive gas turbine plants increase their output, at the expense of the more fuel efficient combined cycle plants, to adjust to the quick solar ramp up during the morning (6-8 AM) and ramp down during the afternoon (7-9 PM). On the other hand, wind power decreased prices during all day with stronger reductions during the afternoon. The authors control for hydropower reallocation using daily aggregate wind and solar generation to explain wholesale hourly prices. Gowrisankaran et al. (2016) also report that solar generation increases the dispatch cost since it requires system operators to reoptimize key decisions and use costly backup generation to deal with intermittency.

The hourly heterogeneous impacts of wind and solar power on prices send signals to smooth their intermittent output by creating arbitrage opportunities for the nascent storage industry. The value of storage is a current active line of research in energy and environmental economics with recent work evaluating the financial and economic benefits of its adoption.

Carson and Novan (2013) estimate marginal emissions based on econometric modelling and use the results along a two-period model of the economics and dynamics of power generation, storage, and emissions to compute the substitution between power sources and the associated social benefits in Texas. They find that electricity arbitrage of low prices in the first hours of the day for high prices in the afternoon increases daily carbon and sulfur emissions since it leads to a substitution of relatively dirty coal generation for clean natural gas. However, private benefits from price arbitrage still exceed the damage caused by emissions substitution.

Holladay and LaRiviere (2018) argue that the negative impacts of bulk storage on emissions are attenuated by declining natural gas prices, while the private arbitrage benefits

become less favorable almost everywhere in the United States. This occurs since natural gas generation with low prices competes with coal for baseload power at night. Hence, the charging hours have lower prices and lower carbon and sulfur emissions than before the fracking boom and the era of cheap gas in the United States. Nevertheless, the authors find that since social costs are still positive, due to the increase in emissions based on 2005 to 2010 data, there is no environmental benefits argument for subsidizing storage.

Giuletti et al. (2018) analyze the profitability of arbitraging wholesale prices with compressed air energy storage in the United Kingdom. Using 2010 to 2015 prices in a detailed daily model, the authors find that for a marginal storer, unable to influence prices, it is profitable to operate the plant (cover operation costs, the assessment did not include construction costs). The most successful strategies buy and sell power mostly twice or thrice during a day, and it is unprofitable to store power over more than one day. The authors argue that additional incentives, such as storage entering the capacity market, are necessary to promote interday arbitrage.

To the best of my knowledge the contributions of this paper are: i) to model the hourly reduction in prices or marginal merit-order effect of solar and wind power by explicitly controlling for the dynamics of hydropower reallocation, ii) to use the econometric reduced form to project how larger solar and wind capacities increase arbitrage opportunities and the profitability of battery storage based on average wholesale prices, and iii) to assess how solar and wind will increase the intermittency and arbitrage opportunities at specific high congestion and price variance nodes.

3. Data

During 2018 and 2019, most power in Mexico came from fossil fuels (79 percent) with combined cycle gas representing slightly more than half of all generation, followed by diesel generation, coal and gas turbine plants (Table 1). Hydropower has an important share of 9 percent on average, and its flexibility can provide valuable smoothing to integrate solar and wind power. The average wholesale market real time price is higher (85.9 and 68.5 USD/MWh in 2018 and 2019, respectively) than those of California and Texas, grids with significant renewable power in the United States, which can be attributed to the high cost of diesel generation and to higher gas prices than in the United States.

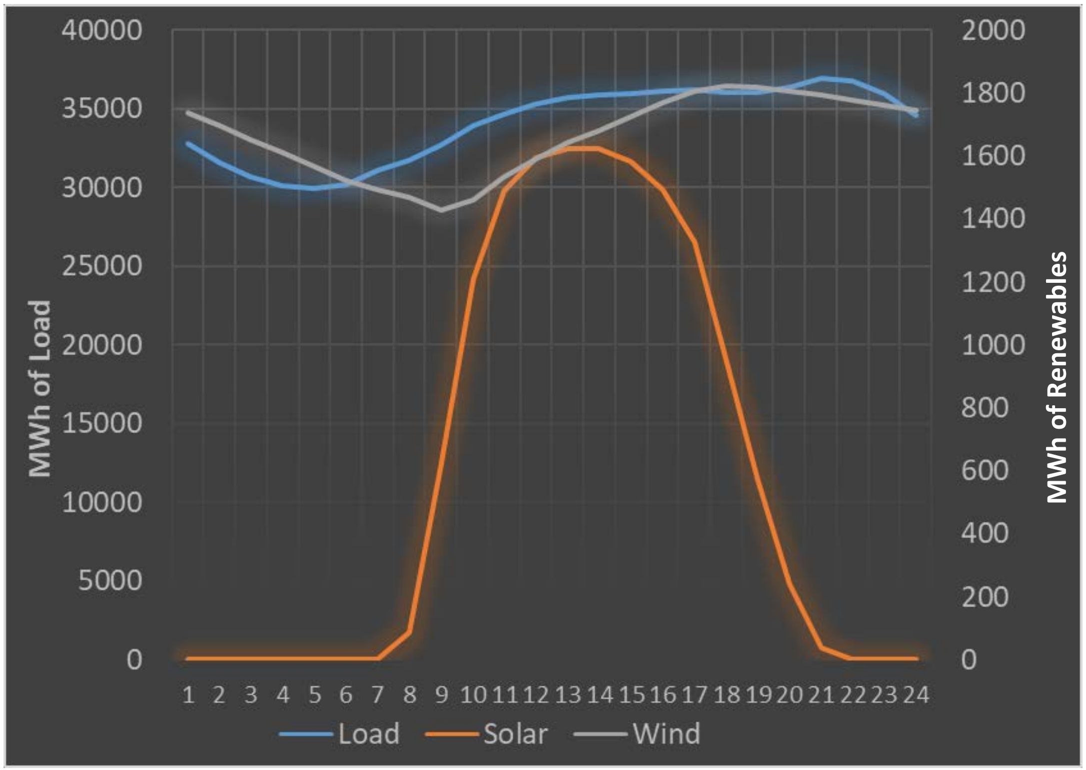
Table 1. Descriptive Statistics of Load and power Generation for 2018-2019 in Mexico

	Mean (MWh)	Standard Deviation (MWh)	Minimum (MWh)	Maximum (MWh)	Generation share	Observations
Demanda	34,056.9	4,429.8	19,396.0	44,563.6		17,518
Eólica	1,663.3	819.2	0.0	4,234.7	5%	17,520
Fotovoltaica	603.0	917.4	-	3,626.4	2%	17,520
Biomasa	10.6	9.0	-	30.5	0%	17,520
Carboeléctrica	2,159.0	680.0	-	4,187.6	6%	17,520
Ciclo Combinado	18,882.5	2,045.1	719.6	24,641.6	53%	17,520
Combustión	326.8	51.2	-	438.2	1%	17,520
Geotérmica	568.9	38.5	225.5	663.5	2%	17,520
Hidroeléctrica	3,183.6	1,913.6	-	10,016.0	9%	17,520
Nuclear	1,374.4	305.5	-	1,590.7	4%	17,520
Térmica	5,167.8	1,590.6	37.1	9,057.7	14%	17,520
Turbo gas	1,889.7	310.8	-	2,800.4	5%	17,520

Source: CENACE, 2019
*Generation data are for the entire country (*Sistema Eléctrico Nacional*), while demand and prices are for the largest subsystem (*Sistema Interconectado Nacional, SIN*).

The share of wind and solar power rose from 5 percent in 2018 to 8.3 percent between 2018 and 2019. Wind provides zero fuel cost power during all hour of the days, and its generation peaks in the afternoon and early evening, supplying the peak demand at those hours (Figure 1). This zero marginal cost generation should have reduced the already high peak wholesale prices (an average of 96.16 USD/MWh from 5-8 pm). Moreover, since hourly wind power generation is positively correlated with load, it should decrease the price gap and arbitrage opportunities from current differences in demand. On the other hand, solar power only reduces morning, midday and afternoon prices. It dwindles from 7 pm onwards, just when demand starts to peak. For this reason, solar power is very likely to increase the current gap in prices and related arbitrage opportunities.

Figure 1. Hourly Average Wind, Solar and Demand for 2018 in Sistema Interconectado Nacional (SIN)



Source: CENACE, 2019

While the publicly available data on generation is for the entire country, I use demand and prices for the largest SIN subsystem since it represents most load in the country (95 percent of national load) and is the largest interconnected grid. The other two systems are much smaller relatively isolated subsystems in which wind and solar power located away would not have much effect on their prices.

4. Hourly Merit-Order Effect Identification and Econometric Specification

To estimate the hourly reductions in wholesale electricity market prices in Mexico's Sistema Interconectado Nacional (SIN) from the incoming wind and solar generation I rely on the exogeneity of hourly renewable power generation. Changes in renewable output are not correlated with the economic decisions that determine power dispatch since they are based on natural cycles and conditions. As depicted in the literature review section, recent work by Novan (2015) and Castro (2019) tests the exogeneity of wind and solar with instrumental variables and find the assumption plausible.

The estimating equation for modelling the hourly marginal merit-order effect is:

$$(1)\; P_t = \sum_{h=1}^{24} \beta_{sh}\, S_t * HOUR_t + \sum_{h=1}^{24} \beta_{wh}\, W_t * HOUR_t + \sum_{h=1}^{24} \beta_{dh}\, D_t * HOUR_t + \sum_{l=0}^{24} \beta_{h-l} Hydro_{t-l} + \delta_w + \varepsilon_t$$

where

P_t stands for the average wholesale electricity market real time price based on all 2,362 nodes in SIN at hour t,

W_t and S_t are aggregate wind and solar power (MWh) in Mexico at hour t,

$Load_t$ is the electricity demand or load (MWh) in SIN at hour t,

$Hydro_{t-l}$ is hydropower generation (MWh) in Mexico at hour t minus lag l,

δ_w stands for weekly fixed effects,

$\boldsymbol{\beta_t}$ are regression coefficients.

The model in equation (1) represents a reduced-form approach to modeling the wholesale market equilibrium prices as a function of the exogenous renewable generation and load as in Novan and Bushnell (2018). Notice that demand or load is also exogenous since end users face fixed monthly and even annual tariffs and not hourly prices reflecting heterogenous marginal generator costs. In this sense, the above model is a reduced-form supply function equation, given no hourly simultaneity in determining demand and generation. I estimate the model using data for all hours in 2018 and 2019 (CENACE, 2020).

The key estimates are $\widehat{\boldsymbol{\beta_{sh}}}$ and $\widehat{\boldsymbol{\beta_{wh}}}$, which represent the hourly marginal merit-order effect or marginal price reductions (USD/MWh) due to an incoming 1 MWh of solar and wind power, respectively. Furthermore, since hydropower represents around 10 percent of all generation there is likely to be some hydro reallocation from the hours with the largest renewable generation to those with the lowest. This hydro shift acts as a battery storage by smoothing the hourly intermittency of wind and solar power (Castro, 2019).

First, I estimate the contemporaneous or static merit-order effect of renewables by not using any hydropower lags at all. Then, I estimate the full or dynamic merit-order effect by using the statistically significant hydropower lags to assess how its reallocation affected the hourly price

reductions. I compute Newey West standard errors accounting for one-day (24 lags) and one-week (168 lags) serial correlation in the time series. I estimate models for pooled 2018-2019 hourly data and also for each year separately.

I also estimate the hourly merit-order effects of renewables at nodes with significant intraday price variability, mostly due to transmission congestion, which constrains the ability to deliver low-cost power from other nodes at peak demand hours with high prices. Using the same estimating equation (1) with hourly prices at the nodal level, I obtain the price effects for the node with the largest and the 50th largest intraday price variabilities. I choose these two nodes to contrast the impact of transmission congestion on the merit-order effect. The node with the largest variability is almost fully congested, and renewables will have a reduced impact on its prices in coming years. The node with the 50th largest variability has some transmission issues but not as critical as the other node. Thus, renewables will likely have a larger influence on its prices as transmission will not be fully saturated.

It is worth noting that the above approach is valid under the current power plant structure and grid configuration in the Sistema Interconectado Nacional (SIN) in Mexico. It cannot capture how prices will respond when more flexible gas generators enter the market to help cope with the intermittency from renewables. Moreover, since the marginal generation cost has an increasing upward slope due to the increasing costs and inefficiencies of peak generators (Reguant, 2018), the marginal merit-order effect of renewables should be decreasing for larger capacities.

Finally, I project how larger wind and solar capacities between 2025 and 2030 determine prices and arbitrage opportunities using the estimates from equation (1) and future wind and solar generation levels. Due to the above explained decreasing impact of renewables on prices, I use the 95 percent confidence interval lower bound estimates based only on the regression with 2019 data. I use the results from the dynamic specification to control for hydropower smoothing and its effects on prices.

Hourly trends in wind and solar capacity factors have been steady from 2018 to 2019 and will be very similar in the future since they are based on their natural cycles. Therefore, hydropower reallocation will have the same effect as the one derived with the dynamic estimates and the heterogeneous hourly merit-order effects of renewables will have the same trend. While new hydropower plants are in the Government's Grid Expansion Plan, they represent a 23.2 percent increase compared to current capacity, but hydro generation declined 26.8 percent between

2018 and 2019 (SENER, 2019; CENACE, 2020). In the future, climate change, competing agricultural, recreational and ecological flow uses make likely a moderate increase in hydro generation and arbitrage from the new plants. Therefore I project future prices based on the smoothing effect of the current plans. This implies that the price and arbitrage opportunities projections contain profits that the new reservoir and even pumped-storage hydropower can exploit as well. For these reasons, the estimates are an upper bound on the effect of solar and wind on prices, and the arbitrage profits inferred from them can also be interpreted as an upper bound.

I obtain the monthly capacity factors from CENACE (2020), which allows me to compute their hourly counterparts using observed generation. Future planned 2025 and 2030 wind and solar capacities come from IMP (2017a and 2017b) and SENER (2019). For example, projected wind and solar generation in 2025 are:

$$(2) S_t^{2025} = Solar\ capacity\ MW_{2025} * Capacity\ factor\ solar\ MWh/MW_t$$

$$(3) W_t^{2025} = Wind\ capacity\ MW_{2025} * Capacity\ factor\ wind\ MWh/MW_t$$

5. Empirical Model for Storage Profits

I use the projected future prices under larger solar and wind capacities to evaluate the profitability of storage. Following Giulietti et al. (2018) I do this assessment for a competitive price taker marginal storer operating at the representative average node, whose size and actions cannot influence average wholesale market prices. This assumption is reasonable for evaluating the profitability of the first pioneer storers whose power arbitrage at particular nodes will not significantly affect the average price of more than 2,000 nodes. Rather, the main force driving price arbitrage opportunities is the increasing intermittency of large renewables expansion. The marginal storer optimization problem is:

$$(4)\ Max_{\boldsymbol{h}} \sum_{24} \widehat{P_t} * h_t$$

$$s.t.\ \ s_{t+1} = s_t - h_t * \left(1 + (\eta - 1) * [1]^{h_{it}<0}\right),\ \ s_0 = 0,\ \ s_t \le s_{max}, |h_t| \le s_{max}$$

where:

s_t is the battery state of charge at hour t,

h_t is charge/discharge action

$\widehat{P}_t$ are the forecasted prices

η is the round-trip efficiency of the battery

Equation (4) states that the storer's objective is to maximize profit subject to the equation of motion of the battery for a one-day horizon. The equation describing the state of charge of the battery shows that charge at the next period s_{t+1} equals the current charge minus the dis(charging) actions h_t discounted by the round-trip efficiency rate. If $h_t < 0$ it represents charging and $h_t > 0$ stands for discharging. The roundtrip efficiency is discounted when charging as in Giulietti et al. (2018). Charging cannot exceed the maximum capacity of the battery s_{max}, which is 1MWh for the marginal storer. The round-trip efficiency is 90 percent following the values used in the literature (Giuletti et al., 2018; De Sisternes et al., 2016).

I simulate two duration types of the battery: 1-hour duration, which corresponds to a medium type, and a long-duration type with 4 hours. These are two conventional types with levelized cost assessments available in the literature (Cole and Frazier, 2019; EIA, 2018).[2] In the case of the 1-hour battery, the same programing of equation (4) applies; while for the 4-hour case the charging constraint is slightly different to reflect that it cannot be fully charged in less than 4 hours $|h_t| \leq \frac{s_{max}}{4}$. To simulate profits for pumped-storage hydropower, I assume that the reservoir will be filled (charged) in 10 hours $\left(\frac{s_{max}}{10}\right)$ based on Sisterne et al. (2016). I simulate battery profits for interday arbitrage (two-day-horizon or t = 48) and compare the results with those of only intraday arbitrage. I simulate the optimal charging profiles for each day of the year using historical and annual forecasted prices.

To evaluate the profitability of the pioneer storers at particular nodes with large intraday price variance and intermittency, usually due to transmission congestion, we can relax the assumption of no price effects. Hence, charging will increase prices since it adds demand and discharging will reduce prices by adding supply. For those cases, I modify the objective of Equation 4 to be $Max_{\boldsymbol{h}} \sum_{24} \left[\left(1 + \varepsilon * \frac{s_{max}}{hour\ charge}\right) * \widehat{P}_t * h_t\right]^{h_t<0} + \left[\left(1 - \varepsilon * \frac{s_{max}}{hour\ charge}\right) * \widehat{P}_t * h_t\right]^{h_t>0}$ where $1 > \varepsilon > 0$ is the price effect estimated at 2.2 percent per MW for individual nodes

[2] The 1-hour duration type refers to a battery whose maximum capacity can be charged in one hour while the 4-hour type is a battery that can be fully charged in 4 hours.

(Kirkpatrick, 2018). I assess the storage arbitrage profits in those high congestion nodes for a 10 MWh battery.

Then I compute the average profit of the storer for each year/scenario. I assume the lifespan of the battery to be 10 years, annual operation and maintenance costs come from recent private sector estimates (Lazard, 2018) and the discount rate is Mexico's *tasa de interés objetivo* in 2019 (8.25 percent).[3] I solve the optimization using the discrete non-linear programming solver of GAMS. Finally, I summarize the hourly (dis)charging actions of the battery for an entire year by clustering similar strategies with the Mixture of Gaussians Unsupervised Machine Learning algorithm in Python.

Equation 2 represents a dynamic optimization problem since it maximizes profit throughout the hours of the day subject to a state variable representing the energy accumulated in the battery. There is no uncertainty related to prices since forecasted prices are taken as fully known from the first hour of the day. Hence, the proposed approach is a dynamic optimization, but it does not explicitly model the uncertainty of prices throughout the day and any option values associated with it.

6. Results

6.1 Hourly Merit-Order Effect Estimates

Wind power reduces wholesale prices all day long, while solar reduces them during the morning, midday and afternoon (Figure 2). Moreover, the contemporaneous or static estimates show that solar power causes significant price increases at sunset due to the additional costs of scheduling and using flexible gas generation to adjust to uncertain supply, as argued and found in previous papers (Gowrisankaran et al., 2016; Bushnell and Novan, 2018).[4] Nevertheless, these price increases are attenuated by hydropower reallocation.

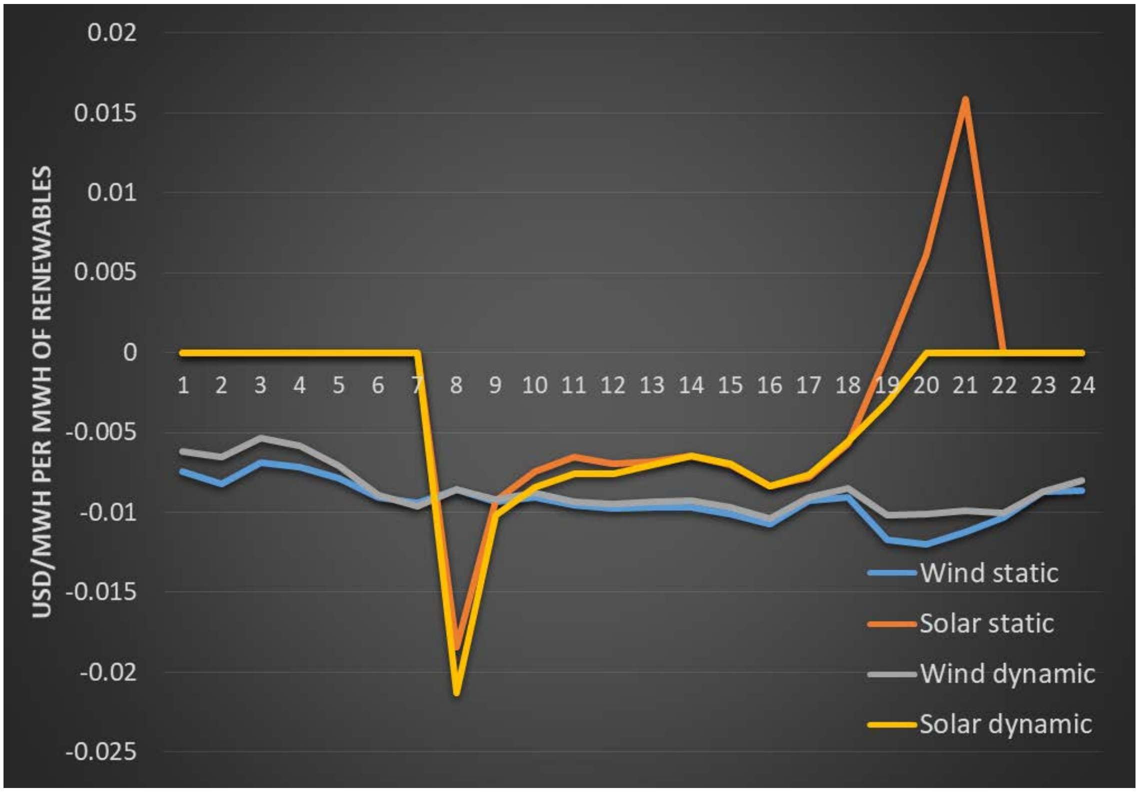
The dynamic model estimates show reduced hourly marginal merit-order effects of solar and wind power. The results confirm that hydropower acts as storage by reallocating generation from the hours with the largest renewable generation to those with the lowest as in California (Castro, 2019). Hence, the price reduction during the morning, midday and early afternoon caused

[3] Operation and maintenance cost is the average of estimates for five Independent System Operators in the U.S. (PJM, ISONE, CAISO, ERCOT, NYISO) (USD 17,304 per MWh)
[4] See Appendix 1

by solar power is attenuated and the shifted hydro is reallocated at sunrise and sunset, when solar generation dwindles, reducing the price increases during those times (Figure 2). Wind power price reductions also decrease, and the shifted hydro reduces the sunset price increase completely (Figure 2). Specifically, from 2018 to 2019, the share of hydropower generation between hours 9 and 18 fell due to the large incoming wind and solar generation. The stored hydro was mostly reallocated to smooth the decline of solar (19-21 hours), as shown in Figure 3. Hence, hydropower smoothed the daily intermittency of renewables and reduced its associated costs.

The most parsimonious dynamic model includes hydropower lags for two, three, 11 and 21 hours ago. The dynamic model is statistically different from its static counterpart as shown by the Wald test of restricted versus unrestricted models ($F_{4,17341} = 43.77$). The robustness checks accounting for 168 lags covering one week show the same results in the static model and the same trend with less significant price reductions in its dynamic counterpart.[5]

Figure 2. Wind and Solar Hourly Merit-Order Effects Estimates for Pooled 2018-2019 Hourly Data (static and dynamic)



*Only statistically significant estimates at 95% confidence interval are displayed.

[5] See Appendix 1.

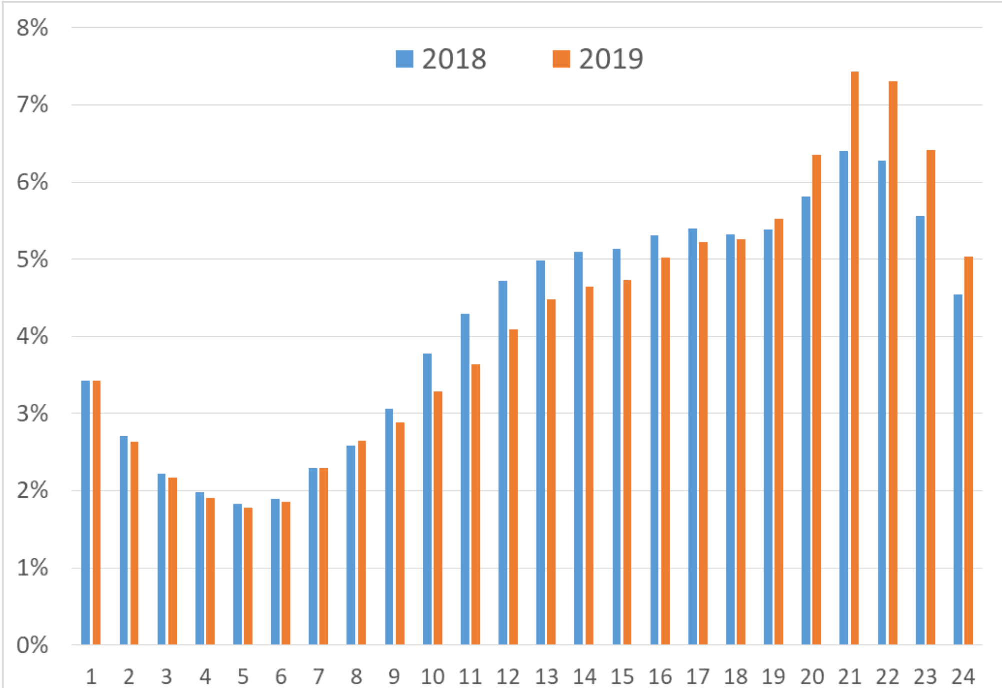
Furthermore, given the increasing slope of the marginal generation cost curve, incoming wind and solar caused lower price reductions in 2019 compared to 2018. However, the same dynamics and hydropower reallocation played a role in both years, decreasing the price reductions from wind to smooth the decline of solar at sunset. Actually, during 2018, solar power actually caused price increases at 20 and 21 hours in spite of hydropower smoothing.[6] But as solar generation grew and the marginal cost of supplying a sudden decrease in its output decreased, in 2019 there were no price increases associated with solar at any time after accounting for hydro reallocation.

As for the merit-order effects at the largest intraday price variance nodes, the hourly price reductions from solar for the node with the 50th largest variance are greater than those of the node with the largest variance of them all.[7] This occurs since the largest variance node is more congested than the 50th node and the increasing renewable generation affects the prices of the former with lower intensity. Thus, without any new transmission lines, prices in the largest variance node are unlikely to respond to new solar capacities as much as prices in the 50th largest node, and there will be more arbitrage opportunities in the latter.

The proposed econometric approach captures power plant start-up costs to the extent that they are incorporated in each hourly bid done by the generators, thereby influencing wholesale equilibrium prices. These start-up costs and rigidities of adjusting fossil generation are behind the rescheduling costs that determine the price increase at sunset in the static or no hydro smoothing estimates. I also estimated models with month-hour and season-hour fixed effects in addition to the weekly fixed effects. The idea was to control for the seasonality of wind and solar generation, as Mexico has four seasons, though not as pronounced as in the United States. However, estimates with those additional fixed effects cannot correctly capture the actual hydropower smoothing dynamics at 20-21 hours (Figure 3) and the associated null price effect in the dynamic regression.

[6] See Appendix 2.
[7] See Appendix 3.

Figure 3. Hourly Shares of Average Daily Hydropower Generation



Source: CENACE, 2019

6.2 Wholesale Prices Projection

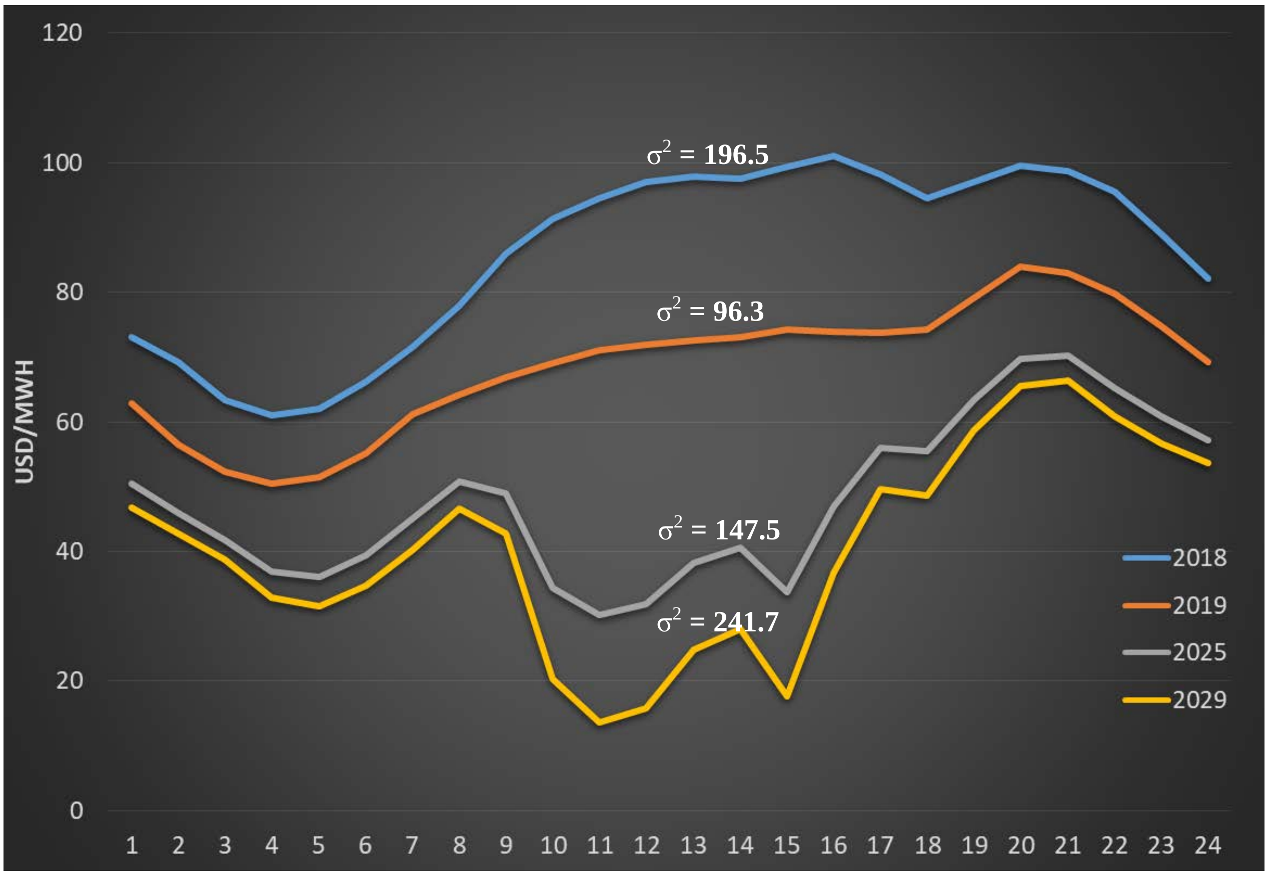
The hourly marginal merit-order effect estimates are interpreted as that, on average, 1 MWh of solar and wind power reduced wholesale electricity prices at 9 AM by 1 and 0.9 USD cents/MWh, respectively.[8] While the point estimates represent a very small fraction of average wholesale prices (< 0.1 percent), the total price reductions due to the large increases in solar and wind generation (287 and 34 percent increments in the average daily generation) have already flattened the price curve from hours 7 to 18 between 2018 and 2019. Moreover, this flattening of the price curve during daylight hours in 2019 actually reduced the variance of average wholesale prices (Figure 4).

Using results from the dynamic model with the 95 percent confidence interval lower bound estimates, I find that since the largest combined renewable generation occurs during daylight, it will create a convex belly in the future years average wholesale prices curve during the midday and increase their variance (Figure 4). The wholesale price curve will resemble the shape and patterns of the "duck curve" with even zero and negative prices as presently occurs with significant

[8] For specific coefficients of all hours see Appendix 1.

solar and wind capacities in California (CAISO, 2016). Even several average hourly prices can be negative for the larger wind and solar capacities planned in 2029 (SENER, 2019), as shown in Figure 5. The heterogeneous hourly merit-order effects of wind and solar on prices will also create several price peaks throughout the day. These peaks reflect the impact of the intermittency of wind and solar, which creates more profitable arbitrage opportunities (Figure 4).

Figure 4. Average Hourly Wholesale Electricity Prices and Variance



Since the estimates and projections are based on the 2018-2019 power plant structure and grid configuration in SIN, the model implies that the 2018-2019 average hourly wholesale prices are equilibrium prices. This assumption also implies that these equilibrium prices will be kept in the long run, absent new renewable capacity, since new fossil capacity will operate to meet increasing demand at the same marginal cost as those plants running in both years. Hence, the increasing wind and solar generation are the only exogenous factors affecting wholesale equilibrium prices.

6.3 Profitability of Storage

Storage profits for energy arbitrage at the wholesale level and based on historical 2018 and 2019 prices are lower than the current range of its levelized cost for both the 1-hour (1,352 USD/kWh) and the 4-hour (380-399 USD/kWh) batteries (EIA, 2018; Fu et al., 2018; Cole and Frazier, 2019). These estimates are for a 90 percent round-trip efficiency battery, meaning that 10 percent of the power withdrawn at one hour is lost and cannot be added at a later time (Table 2). Arbitrage profits decline in 2019 due to the combined wind and solar generation flattening the price curve and reducing its variance during daylight as discussed in previous sections.

While I use the conservative 95 percent confidence interval lower bound price effect for projecting future values, the merit-order effect of renewables could be lower when the planned new hydropower plants start operating and arbitrage away some of those price differences. Therefore, while the estimates capture current hydropower smoothing trends, which might become larger with new reservoir capacity, the projections reflect the arbitrage potential that can also be tapped by new reservoir and even pumped-storage hydropower.

Under larger future wind and solar capacities in 2025 and 2029, energy arbitrage profits increase ranging from 115.6 to 225 USD/kWh (Table 2). For the 4-hour battery, profits are within the projected range of future levelized storage costs by 2029 (136-307 USD/kWh) with solar and wind supplying 23.5 percent of load (Cole and Frazier, 2019; IRENA, 2017). Assessing storage profits under interday arbitrage (two-day-horizon) does not significantly alter the results: for the 4-hour battery with 2025 prices, profits are almost identical (115.84 USD/kWh). Therefore, handling the intermittency of significant wind and solar power can become financially viable and support the delivery of reliable clean power.

Table 2. Storage Profits under Different Wind and Solar Capacities

		2018	2019	2025	2029
Profit storage USD/kWh	**1 hr**	149.44	101.94	186.85	225.06
	4 hr	104.36	74.53	115.66	145.88
Wind	**GW**	4.7	5.9	12.7	14.7
	% Load	4.20%	5.5%	11.8%	12.5%
Solar	**GW**	1.8	4.7	12.7	16.2
	% Load	0.70%	2.8%	9.4%	11%

*Wind and solar shares of load are based on projected demand by (Yépez et al., 2018).
*USD/kWh are in nominal values.

However, storage profits can be larger and become viable sooner, and under lower wind and solar capacities, if we consider other services such as frequency regulation and demand charge management. In fact, frequency regulation accounts for 14 to 86 percent of the potential revenue and cost savings of battery storage systems in four of the U.S. Independent System Operators (Lazard, 2018). While the declining marginal merit-order effect under larger renewables capacities and the larger hydropower smoothing of future reservoir plants make the storage arbitrage profits an upper bound, not adding the value of other services make these projections a conservative appraisal of the full profitability of the first pioneer storers.

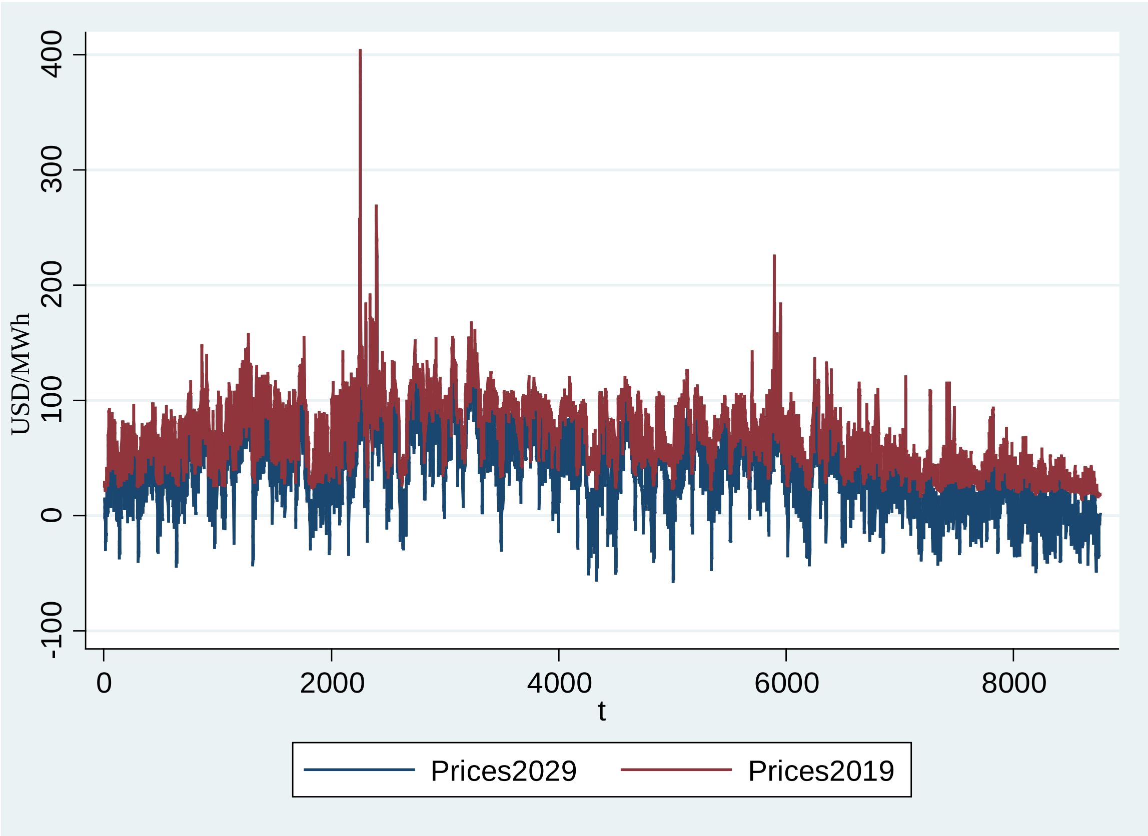
Since the price variance is larger at congested nodes, the arbitrage profitability will be higher for the 50th largest intraday price variance node. Moreover, for this node, arbitrage profits for the 4-hour battery (170.5 USD/kWh) can cover its LCOE sooner by 2025 (160-318 USD/kWh) and under lower renewables intermittency and capacity than for the average node. On the other hand, the node with the largest intraday price variance is almost fully congested and with a lower impact of renewables on its prices. Thus, arbitrage profits in this node by 2025 (99.37 USD/kWh) can be even a bit lower than those based on average wholesale prices and not within the range of the LCOE of storage.

While for the largest variance node, transmission can alleviate congestion and bring the impact of renewables on arbitrage to the same level than at the average node; for the 50th largest variance node it could also reduce congestion but reduce price variability and the profitability of storage. Hence, storage and transmission investments have complementarities and tradeoffs for arbitraging nodal price differences. Policymakers need to explicitly consider these issues with both technologies and plan accordingly to deliver the most cost-effective and clean grid configuration. Even if improving transmission can reduce all spatial nodal price differences, the intraday price differences and intermittency reflected at the wholesale level will very likely increase for larger wind and solar capacities as shown by the projections.

Pumped-storage hydropower would cover its LCOE (100-250 USD/kWh based on De Sisternes et al., 2016) by 2030 (15.9 GW of wind and 17.5 GW of solar) since it arbitrages power at a lower rate than even the 4-hour battery. Moreover, since pumped-storage is a mature technology, its LCOE is not likely to experience reductions as significant as those of batteries. In contrast to the batteries, this technology cannot be specifically located at those nodes with high

intermittency. Rather, it is located based on natural site feasibility. For this reason, I used average wholesale prices to evaluate its profits, which are 5 percent higher for the two-day horizon due to its lower charging rate and larger duration (105.9 USD/kWh).

Figure 5. Year-Round Hourly Wholesale Electricity Prices (historical and projections)



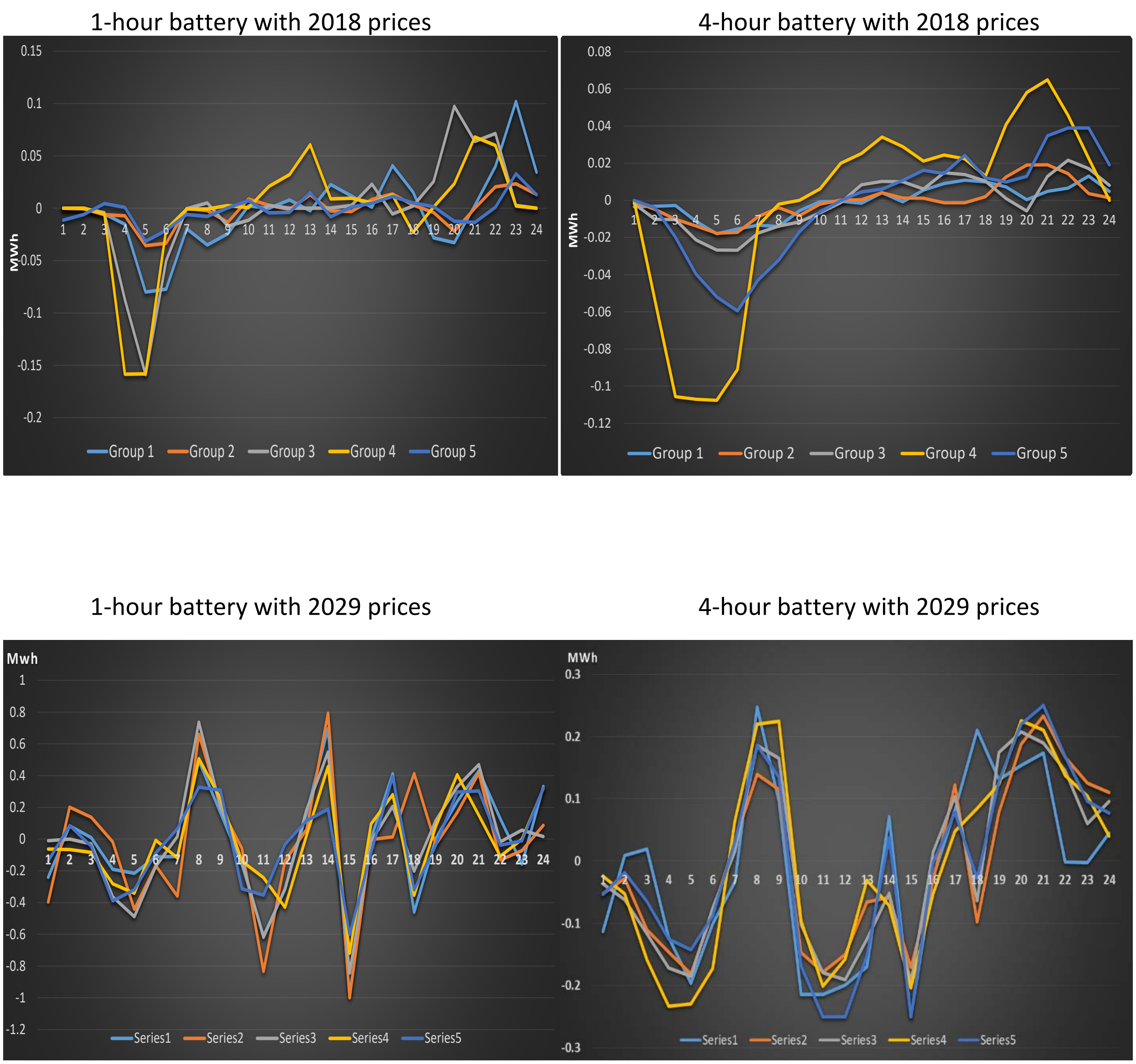
The charging profile varies by day depending on the specific renewable energy and demand realizations which determine price arbitrage opportunities (Figure 5). There are days in which storage arbitrages twice, day and afternoon-night, and other days in which it arbitrages continuously throughout the day.[9] On average, the battery charges during the first hours of the day (3-6) and mostly serves the evening and night peak demand (17-22), and sometimes the midday peak (12-13). The charging strategy groups have similar profiles for the 1-hour and 4-hour duration cases, but for the former it has more cycles with quicker charging and discharging which lead to

[9] See Appendix 4 for specific charging profiles.

larger profits (Figure 6). As argued previously, those larger profits are not as close to the levelized cost of storage as for the 4-hour battery.

The profit-maximizing storer arbitrages energy all days of the year even under the 2018 wind and solar capacities and price levels. As renewables supply more power, their intermittency and arbitrage opportunities increase, and the storer arbitrages even more energy during all days of the year. Hence, the charging strategy clusters show more cycles throughout the day with 2029 prices, charging and releasing power continuously, and as with 2018 prices, the shorter duration 1-hour battery can arbitrage more energy than its counterpart.

Figure 6. Clusters of Daily Optimal Charging and Discharging Actions



7. Discussion

This paper has argued that wind and solar power have hourly heterogenous impacts on wholesale prices and that solar power can even increase prices during sunrise and sunset. This finding is in line with previous results by Bushnell and Novan (2018) in California, where solar power also increased wholesale prices at sunrise and sunset. While their work controls for hydro reallocation indirectly by assessing the effect of aggregate daily solar and wind on hourly prices, I explicitly control for hydro reallocation using lags in a dynamic model. Hence, I was able to show how hydropower attenuated the static price increase during sunrise and slightly reduced the increase at sunset.

As argued previously, shifting generation from hours with high renewable generation to those with low, reservoir hydropower reallocation smoothed the intermittency of solar power. Moreover, this reallocation shows that hydro already acts as a battery, reducing total generation costs and delivering value to customers. Hydropower can smooth intermittency and help to integrate renewables by arbitraging power as long as there are no severe constraints (irrigation, flow limits) limiting when it can be used (Archsmith, 2018).

Similar to Giuletti et al. (2018) I found that storage is not profitable if it only relies on arbitrage revenue for the current low intermittency wind and solar levels, and that interday arbitrage does not increase storage profitability. Nevertheless, I argue that for certain high congestion nodes, price variation will be large enough to render profits that surpass the levelized cost of battery storage sooner than for the average wholesale price based on all nodes. I go beyond the literature in forecasting future prices under larger renewables capacity, at the average and high variance nodes. Since interday arbitrage will not increase profits significantly, at the nascent stage of the storage industry in Mexico, batteries will mostly arbitrage energy within the same day.

The price projections presented in the results are based on an econometric reduced form that captures a supply equation with exogenous load, renewable generation and time fixed-effects. The captured relationship is for an equilibrium in power plant investment, entry and exit. The model assumes that plants operating in 2019 will continue to operate under larger solar and wind capacities in 2025 and beyond. I do not explicitly model how reduced payments, from low and negative prices, and hours of operation affect power plant revenue, exit, entry and investment. Nor

do I model how more flexible generation can alter prices. Having several negative prices is certainly of concern to the cost recovery and operation of traditional fossil fuel generators and to the resource adequacy of the system. For this reason, it merits further research of its own.

I evaluate the profitability and feasibility of the first pioneer storers whose power arbitrage at particular nodes will not significantly affect the average price of more than 2,000 nodes. While the projected profits can decrease with the entrance of large storage capacities, this increase is unlikely to reduce arbitrage gains below the levelized cost. Otherwise, the entrant storers would incur losses. Moreover, storage profits for the pioneer entrants can be secured as long as the arbitrage by new batteries does not erase the gains coming from increasing solar and wind intermittency. Of course, formally modelling the dynamics of battery cost reductions, entry by new storers and government planned renewables expansion would add more complications and nuances to the analysis, but this is beyond the scope of this paper. The projected price distribution and the associated future storage profits are valid under a national scenario with no significant national and international new transmission lines and no major changes in demand profiles.

While my goal was assessing the current and projected profits of a marginal storer, the value of storage depends on all the services it can offer, the externalities it can exacerbate or mitigate, its total impact on welfare, and the dynamics of new storers entry (Holladay and LaRiviere, 2018). Furthermore, having competitive wholesale generation markets is a necessary condition to avoid overinvestment in battery storage and inefficiencies in arbitrage (Siddiqui et al., 2019; Schmalensee, 2019).

The insights from this research on wind and solar intermittency increasing price variability and arbitrage profits can also be extrapolated to other countries in Latin America and the Caribbean (Argentina, Chile) and worldwide with increasing shares of renewables and non-dominant hydropower. The reduced form econometrics and dynamic optimization methods proposed in this paper could be a feasible methodology to assess the impact of renewables on those grids. The exact quantities and trends will depend on the correlation between renewables and demand and the capacity of wind and solar.

8. Conclusions

As renewables supply a larger share of electricity demand, storage becomes key for dealing with their intermittency and delivering reliable power. In Mexico, wind power is complementary to

demand since its generation peaks in the afternoon and evening when the lights come on. Hence, the zero-fuel-cost wind reduces wholesale prices during those hours. On the other hand, solar power reduces prices during the day increasing the price gap between off-peak and peak demand hours.

Therefore, the combined intermittency of solar and wind increase wholesale price variation and create opportunities for buying power when prices are low, storing it in batteries and selling it back when prices are high. Based on 2019 wind and solar capacities (both serving 8.3 percent of demand), storage arbitrage profits at the wholesale level are lower than the current range of its levelized cost for 1-hour and 4-hour batteries. However, total profits can be larger if the battery offers other services, such as frequency regulation and capacity.

As wind and solar provide more power to the grid, their intermittency increases, creating more profitable arbitrage opportunities for batteries in the coming years. For the government 2025 goal of wind (12.7 GW) and solar (12.7 GW) capacities, these profits can be within the projected range of its future levelized costs for a 4-hour battery located at nodes with large price variability and transmission congestion. For prices based on the averages of all nodes, profits can cover the LCOE for the 4-hour battery by 2029 and by 2030 for pumped-storage hydropower.

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Appendix 1. Static and Dynamic Hourly Merit-Order Effect Estimates for pooled 2018-2019 hourly data

VARIABLES	Dynamic 24 hour lags	Dynamic 168 hour lags	Static 24 hour lags	Static 168 hour lags
1b.hour#c.X_Eolica	-0.00617***	-0.00617***	-0.00743***	-0.00743***
	(0.000895)	(0.00138)	(0.000906)	(0.00143)
2.hour#c.X_Eolica	-0.00655***	-0.00655***	-0.00820***	-0.00820***
	(0.000847)	(0.00127)	(0.000841)	(0.00130)
3.hour#c.X_Eolica	-0.00534***	-0.00534***	-0.00690***	-0.00690***
	(0.000866)	(0.00134)	(0.000871)	(0.00139)
4.hour#c.X_Eolica	-0.00586***	-0.00586***	-0.00714***	-0.00714***
	(0.000835)	(0.00131)	(0.000863)	(0.00139)
5.hour#c.X_Eolica	-0.00710***	-0.00710***	-0.00787***	-0.00787***
	(0.000806)	(0.00124)	(0.000853)	(0.00133)
6.hour#c.X_Eolica	-0.00891***	-0.00891***	-0.00905***	-0.00905***
	(0.000806)	(0.00118)	(0.000841)	(0.00125)
7.hour#c.X_Eolica	-0.00963***	-0.00963***	-0.00940***	-0.00940***
	(0.000829)	(0.00117)	(0.000845)	(0.00121)
8.hour#c.X_Eolica	-0.00858***	-0.00858***	-0.00855***	-0.00855***
	(0.000786)	(0.00105)	(0.000809)	(0.00108)
9.hour#c.X_Eolica	-0.00919***	-0.00919***	-0.00931***	-0.00931***
	(0.000739)	(0.000925)	(0.000751)	(0.000930)
10.hour#c.X_Eolica	-0.00878***	-0.00878***	-0.00904***	-0.00904***
	(0.000794)	(0.00112)	(0.000788)	(0.00110)
11.hour#c.X_Eolica	-0.00933***	-0.00933***	-0.00957***	-0.00957***
	(0.000784)	(0.00107)	(0.000769)	(0.00106)
12.hour#c.X_Eolica	-0.00951***	-0.00951***	-0.00976***	-0.00976***
	(0.000806)	(0.00103)	(0.000797)	(0.00103)
13.hour#c.X_Eolica	-0.00933***	-0.00933***	-0.00965***	-0.00965***
	(0.000890)	(0.00106)	(0.000880)	(0.00107)
14.hour#c.X_Eolica	-0.00929***	-0.00929***	-0.00968***	-0.00968***
	(0.000926)	(0.00111)	(0.000903)	(0.00110)
15.hour#c.X_Eolica	-0.00966***	-0.00966***	-0.0101***	-0.0101***
	(0.000925)	(0.00124)	(0.000906)	(0.00122)
16.hour#c.X_Eolica	-0.0104***	-0.0104***	-0.0107***	-0.0107***
	(0.00114)	(0.00139)	(0.00112)	(0.00139)
17.hour#c.X_Eolica	-0.00906***	-0.00906***	-0.00926***	-0.00926***
	(0.000977)	(0.00120)	(0.000974)	(0.00123)
18.hour#c.X_Eolica	-0.00849***	-0.00849***	-0.00904***	-0.00904***
	(0.00108)	(0.00126)	(0.00108)	(0.00128)
19.hour#c.X_Eolica	-0.0102***	-0.0102***	-0.0117***	-0.0117***
	(0.00110)	(0.00139)	(0.00109)	(0.00138)
20.hour#c.X_Eolica	-0.0101***	-0.0101***	-0.0120***	-0.0120***
	(0.00110)	(0.00121)	(0.00114)	(0.00120)

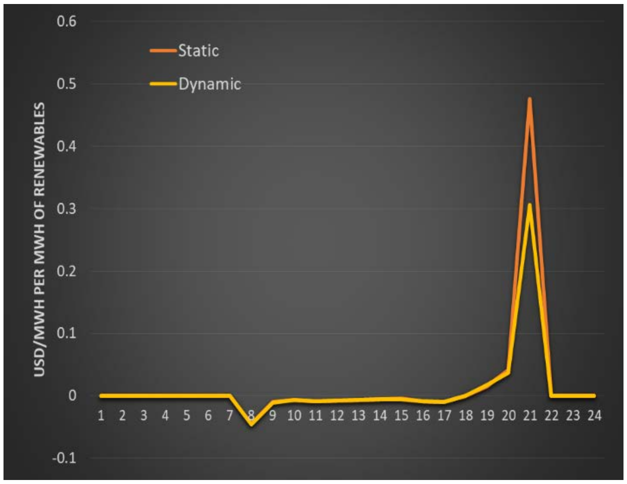
21.hour#c.X_Eolica	-0.00987***	-0.00987***	-0.0112***	-0.0112***
	(0.00101)	(0.00114)	(0.00103)	(0.00117)
22.hour#c.X_Eolica	-0.0100***	-0.0100***	-0.0103***	-0.0103***
	(0.00103)	(0.00111)	(0.00104)	(0.00111)
23.hour#c.X_Eolica	-0.00874***	-0.00874***	-0.00872***	-0.00872***
	(0.000977)	(0.00114)	(0.00101)	(0.00121)
24.hour#c.X_Eolica	-0.00798***	-0.00798***	-0.00861***	-0.00861***
	(0.000939)	(0.00117)	(0.000956)	(0.00121)
1b.hour#c.X_Fotovoltaica	-1.615	-1.615	-2.026	-2.026
	(3.118)	(3.507)	(3.322)	(3.951)
2.hour#c.X_Fotovoltaica	0.623	0.623	-0.784	-0.784
	(4.063)	(3.959)	(4.380)	(4.445)
3.hour#c.X_Fotovoltaica	4.624	4.624	3.807	3.807
	(4.789)	(4.784)	(5.612)	(5.931)
4.hour#c.X_Fotovoltaica	5.252	5.252	6.359	6.359
	(8.945)	(9.040)	(9.780)	(10.17)
5.hour#c.X_Fotovoltaica	3.644	3.644	3.238	3.238
	(9.124)	(9.505)	(9.133)	(9.740)
6.hour#c.X_Fotovoltaica	7.527	7.527	7.550	7.550
	(7.911)	(8.772)	(7.877)	(8.576)
7.hour#c.X_Fotovoltaica	0.0963	0.0963	0.0958	0.0958
	(0.178)	(0.220)	(0.164)	(0.196)
8.hour#c.X_Fotovoltaica	-0.0213***	-0.0213***	-0.0184***	-0.0184***
	(0.00564)	(0.00513)	(0.00543)	(0.00482)
9.hour#c.X_Fotovoltaica	-0.0102***	-0.0102***	-0.00925***	-0.00925***
	(0.00124)	(0.00140)	(0.00123)	(0.00143)
10.hour#c.X_Fotovoltaica	-0.00843***	-0.00843***	-0.00744***	-0.00744***
	(0.000798)	(0.00108)	(0.000822)	(0.00116)
11.hour#c.X_Fotovoltaica	-0.00756***	-0.00756***	-0.00656***	-0.00656***
	(0.000691)	(0.000842)	(0.000707)	(0.000932)
12.hour#c.X_Fotovoltaica	-0.00760***	-0.00760***	-0.00699***	-0.00699***
	(0.000683)	(0.000764)	(0.000698)	(0.000835)
13.hour#c.X_Fotovoltaica	-0.00700***	-0.00700***	-0.00681***	-0.00681***
	(0.000803)	(0.000976)	(0.000827)	(0.00105)
14.hour#c.X_Fotovoltaica	-0.00645***	-0.00645***	-0.00647***	-0.00647***
	(0.000665)	(0.000744)	(0.000691)	(0.000836)
15.hour#c.X_Fotovoltaica	-0.00695***	-0.00695***	-0.00704***	-0.00704***
	(0.000717)	(0.000906)	(0.000756)	(0.000982)
16.hour#c.X_Fotovoltaica	-0.00835***	-0.00835***	-0.00838***	-0.00838***
	(0.000867)	(0.00122)	(0.000904)	(0.00130)
17.hour#c.X_Fotovoltaica	-0.00768***	-0.00768***	-0.00780***	-0.00780***
	(0.000871)	(0.00111)	(0.000918)	(0.00121)
18.hour#c.X_Fotovoltaica	-0.00556***	-0.00556***	-0.00567***	-0.00567***
	(0.000800)	(0.000792)	(0.000753)	(0.000771)
19.hour#c.X_Fotovoltaica	-0.00309***	-0.00309***	-0.00130	-0.00130
	(0.000911)	(0.00115)	(0.000887)	(0.00123)

20.hour#c.X_Fotovoltaica	0.000399	0.000399	0.00611***	0.00611***
	(0.00179)	(0.00209)	(0.00167)	(0.00234)
21.hour#c.X_Fotovoltaica	0.00408	0.00408	0.0159**	0.0159***
	(0.00715)	(0.00651)	(0.00616)	(0.00541)
22.hour#c.X_Fotovoltaica	0.297	0.297	0.203	0.203
	(0.188)	(0.206)	(0.216)	(0.239)
23.hour#c.X_Fotovoltaica	0.487	0.487	0.844*	0.844*
	(0.381)	(0.379)	(0.447)	(0.477)
24.hour#c.X_Fotovoltaica	-0.403	-0.403	-0.367	-0.367
	(0.484)	(0.436)	(0.548)	(0.492)

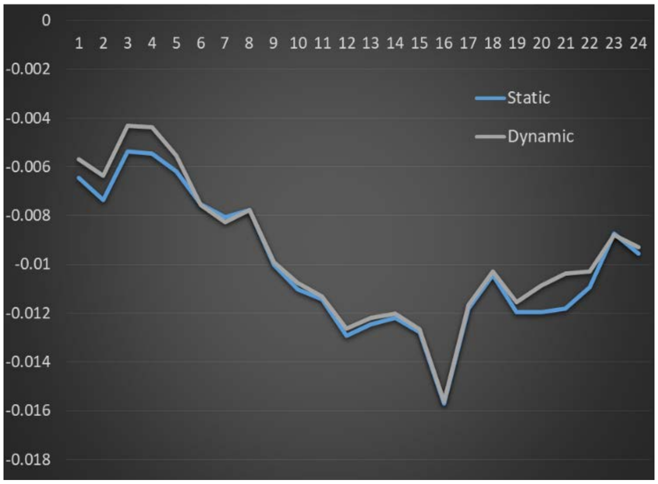
Significance levels: ***99%, **95%, *90%

Appendix 2. Wind and Solar Hourly Merit-Order Effects Estimates for Each Year

2018 Solar merit-order estimates

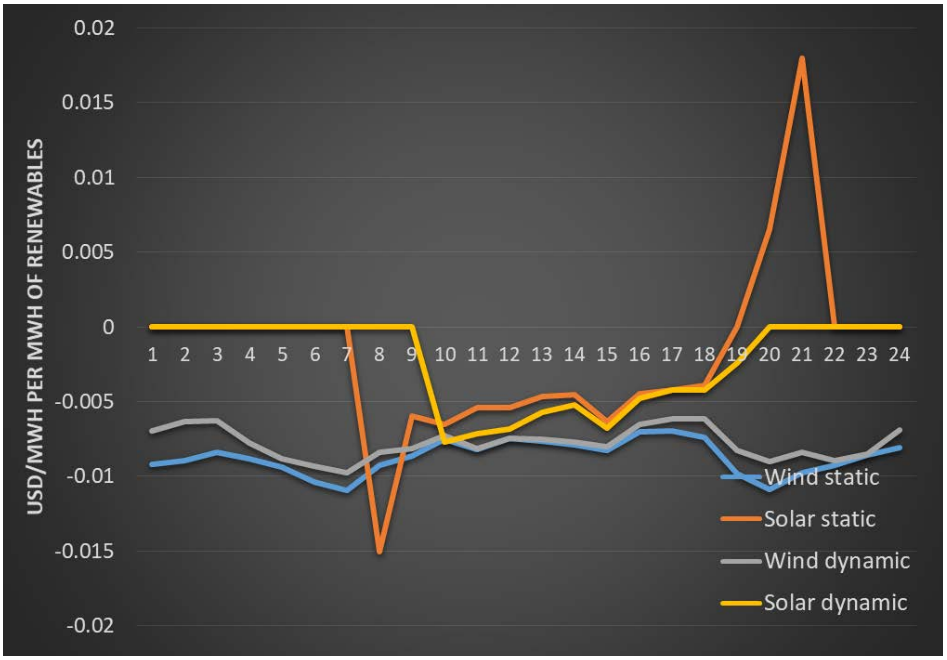


2018 Wind merit-order estimates



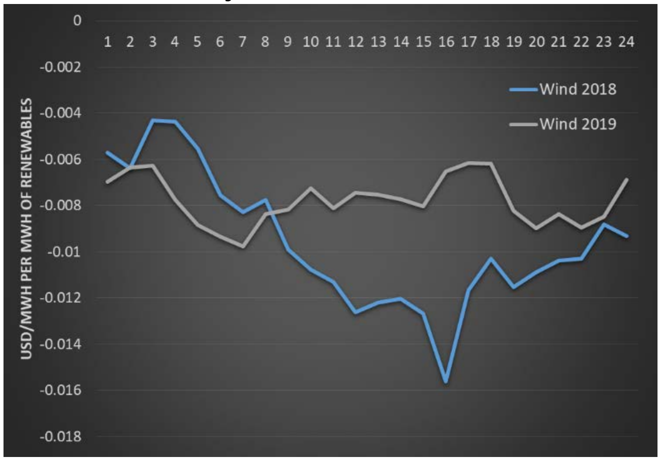
*Only statistically significant estimates at 95% confidence interval are displayed.

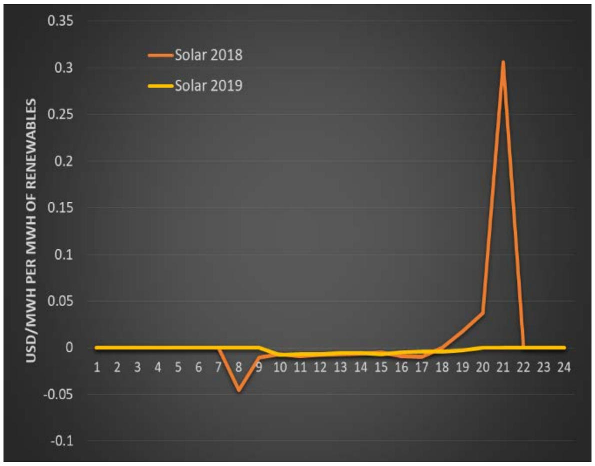
2019 Solar and wind merit-order estimates



*Only statistically significant estimates at 95% confidence interval are displayed.

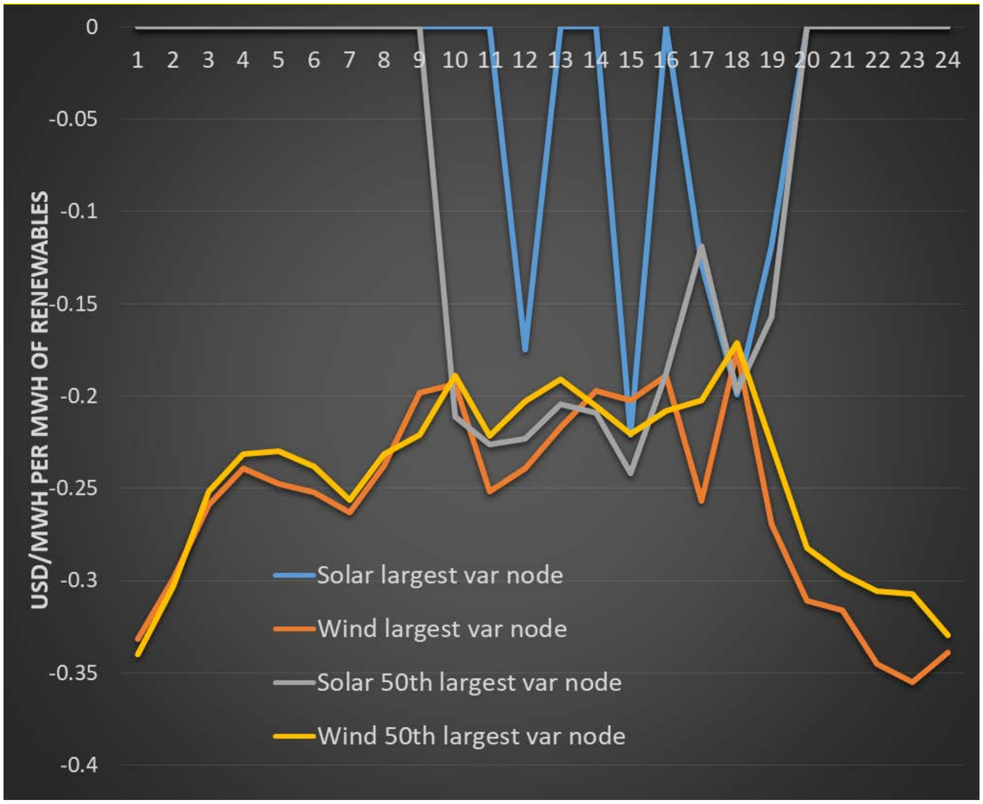
2018 and 2019 dynamic merit-order estimates





*Only statistically significant estimates at 95% confidence interval are displayed.

Appendix 3. Wind and Solar Dynamic Hourly Merit-Order Effect Estimates for the Largest Intraday Price Variance Node and the 50th-Largest Intraday Price Variance Node

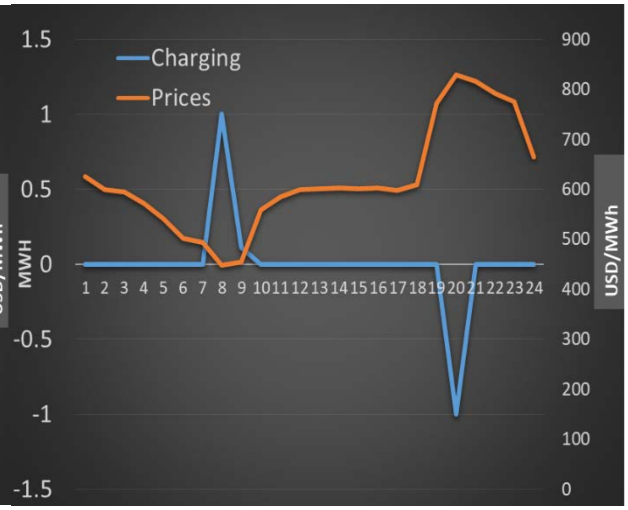


*Only statistically significant estimates at 95% confidence interval are displayed.

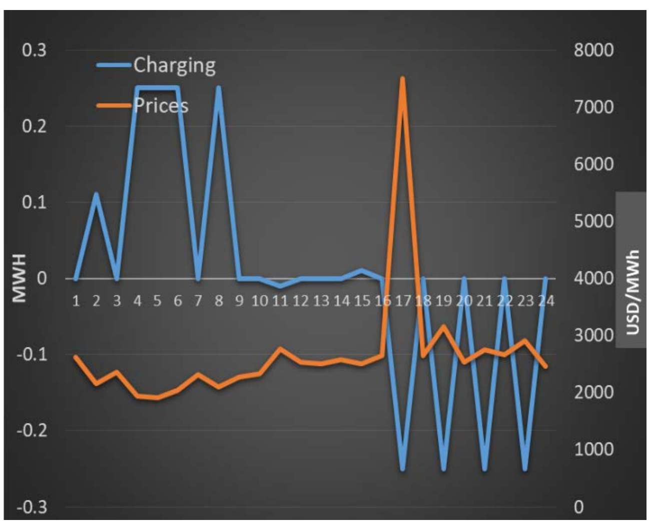
Appendix 4. Optimal Charging and Discharging Actions along Daily Price profiles

2018 1-hour duration

2018 1-hour duration



2018 4-hour duration



2018 4-hour duration