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Research Article

The impact of variable renewable energy resources on power system reliability

Amanda J. Harker Steele [a,*], J. Wesley Burnett [b], John C. Bergstrom [c]

[a] Senior Economist, KeyLogic Systems LLC, 3168 Collins Ferry Rd., Morgantown, WV, 26505, USA
[b] Department of Economics, College of Charleston, 5 Liberty Street, 423 Beatty Center, Charleston, SC, 29401, USA
[c] Department of Agricultural and Applied Economics, University of Georgia, 208c Conner Hall, 147 Cedar St., Athens, GA, 30602, USA

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ABSTRACT

Transitioning the electric power sector to rely more on wind and solar photovoltaics (WPV) has long been cited as a potential solution to reducing harmful greenhouse gas emissions associated with fossil fuel electricity production. An under-explored implication of this transition, however, is whether increasing the amount of net generation supplied by WPV negatively impacts power system reliability? In this paper, we empirically investigate the preceding question using an unbalanced panel dataset of utility-scale operations between 2013 and 2017. Disruptions in power system reliability are measured by the frequency and duration of power system disruptions experienced by end-consumers. Results suggest net generation from WPV, on average, has a significant positive impact on the length of power system disruptions experienced, but only at low levels of net generation from WPV. As net generation from WPV increases, the duration of power system disruptions decreases. To provide insight into the policy implications of these results, we forecast disruptions in power system reliability, assuming different renewable energy policy scenarios for states across the United States with active renewable support policies in place. We estimate the economic costs of forecasted disruptions using an open-source, interruption cost estimate calculator.

1. Introduction

Extreme weather events, including major hurricanes along the eastern and Gulf coasts, freezing weather in the Northeast, and uncontrollable wildfires in the West continue to reveal the potential risks to power system reliability.[1] In addition to mitigating these potential risks, electric power system operators face the ongoing challenge of ensuring the current grid system has adequate infrastructure to keep pace with the increasing penetration of renewable energy resources, including wind and solar photovoltaics (WPV).[2,3]

In response to rapid technological advancement, falling energy prices, and evolving regulatory environments, over the past decade grid

* Corresponding author.
E-mail addresses: ajharkersteele@gmail.com (A.J. Harker Steele), burnettjw@cofc.edu (J.W. Burnett), jberg@uga.edu (J.C. Bergstrom).

[1] It is estimated that Superstorm Sandy inflicted nearly $70 billion USD in damages and left over eight million customers across twenty-one states without power for multiple days and weeks (Henry and Ramirez-Marquez, 2016). In preparation for potential wildfires in the West, Pacific Gas and Electric (PG&E) shut-off power to over 940,000 homes and businesses in California – leaving nearly 2.7 million people without power (Newburger 2019).

[2] As penetration of WPV continues to grow, the electric utility sector will have to adapt to new requirements for electrical interconnection, utility rate tariffs, and franchise rights to accommodate the growing number of renewable generators. In addition, increased capacity being generated by customers (i.e., behind the meter resources) will require additional infrastructure along the grid that allows for the two-way flow of power being generated. This study does not consider behind-the-meter resources as contributors to net generation supplied by WPV.

[3] The term WPV and distributed energy resources (DERs) are often used interchangeably when analyzing topics related to electric power generation. The two terms, however, are in fact different. The term WPV refers to any electricity generating resources whose output is not perfectly controllable/predictable (Bird et al., 2013). The term DERs refers to any electricity generating resource that is directly located on the distribution system and could partially or completely offset customer demand (FERC, 2018). Examples of DERs include “at home” installations of wind or solar photovoltaics, energy efficiency investments, demand response resources (FERC, 2018).

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systems powered by WPV have proliferated across the United States (U.S.).[4] While WPV provide an opportunity to reduce the greenhouse emissions associated with traditional fossil fuel electricity generation, their inherent variable nature has raised some questions within the energy policy literature. Perhaps the most important of which are: 1) Does increasing the amount of the net generation supplied by WPV negatively impact power system reliability? and 2) If so, then what are the economic costs associated with decreased reliability of the power system?

This paper helps to answer these two interrelated questions by empirically examining whether increasing the amount of utility-scale net generation from WPV influences the frequency or duration of disruptions in power system reliability experienced by end-consumers. For the purposes of this study, we assume electrical system reliability can be defined as the ability of the electrical grid generating system and its components to provide a consistent, steady, uninterrupted supply of power to end-consumers. To investigate this relationship, we compiled data from two annual surveys administered by the U.S. Energy Information Administration (EIA). This dataset consists of an unbalanced panel of disruptions experienced by end-use customers and electric utility operational information, including net generation supplied by WPV between 2013 and 2017.

A random-effects model specification was used to estimate the effect of increasing net generation supplied by WPV on the frequency and duration of disruptions experienced by end-consumers. We used an instrumental variables (IV) specification to control for the potential endogeneity between the amount of net generation supplied by WPV, which is likely affected by a state's policy support for renewable electricity generation, and the frequency and duration of disruptions experienced. Commonly used test statistics confirmed the validity of the chosen instruments.

Empirical results suggest net generation supplied by WPV has had, at the margin, an economically small but statistically significant impact on the duration of disruptions experienced by end-consumers. Based on these findings, we forecast the near-term future economic costs associated with potential disruptions for states across the United States (U.S.) with current renewable support policies in place. Cost estimates are generated from the Interruption Cost Estimate (ICE) Calculator (Sullivan et al., 2018). Results suggest, as the net capacity supplied by WPV increases, the total cost of sustained power system interruptions ranges from $1.5 million U.S. Dollars (USD) to $2.5 trillion USD. The cost per unserved kilowatt-hour of electricity ranges from $29 to $160 USD.

Our particular study is critical because the grid system is still in its infancy regarding the shift towards non-centralized generation. Yet next to natural gas, newly installed electric capacity is projected to come primarily from wind and solar (U.S. Energy Information Administration (EIA), 2020). Furthermore, as Clearly and Palmer (2019) and Imedla et al. (2018) suggest, as generation from renewables increases, early identification of potential vulnerabilities (i.e., extreme weather, insufficient infrastructure) is critical to ensuring grid system failures are minimized. To this note, our study makes an important contribution to the literature by providing an early analysis of the vulnerability of the power grid system to disruptions in service reliability resulting from increased net generation from WPV.

The remainder of this paper is organized as follows. Section 2 provides an overview of recent literature related to our research. Section 3 provides background context for our empirical analysis. Section 4 provides a detailed explanation of how we measure disruptions in the reliability of service, describes the data used for our empirical analysis, and explains our empirical approach. Section 5 discusses the results of our study. We conclude in Section 6 by providing a summary of the main findings, discussing the policy implications of this work, and potential future work from this research.

2. Literature review

Much of the prior published work related to electric grid system reliability has focused on uncovering time-trends in bulk power system (BPS) interruptions, which have implications for public policy and investment decisions surrounding the revitalization of the U.S. electrical grid (Eto and LaCommare 2008; Hines et al., 2009; Larsen et al. 2015, 2016).[5] Past findings suggest most adverse system interruptions, when and if they do occur, occur at the distribution level (Hines et al., 2009; Eto et al., 2012). Following suggestions from Eto et al. (2012), this study focused on disruptions experienced at the distribution-level by end-consumers resulting from increased net generation from WPV.

Burtraw et al. (2013) addressed reliability concerns brought about by U.S. public policy initiatives designed to reduce the amount of GHG emissions produced from electricity generation. Their results suggest regulations lead to investments in pollution control technologies, which provide the opportunity for utilities to reduce the emissions associated with traditional fossil-fuel power generation without necessarily changing inputs.[6] Burtaw et al.'s (2013) findings raise the question: What happens when the energy resource inputs used to generate electricity are altered to achieve emissions reductions targets?

This fundamental question has been considered in the engineering literature for some time now. A somewhat recent example includes Wangdee (2014), who uses a systems well-being-analysis framework to investigate the effect of adding wind capacity to a generating system that has historically relied on traditional fossil fuels. Wangdee's (2014) primary analysis is theoretical, which demonstrates the gap in the literature to empirically examine system reliability implications as net generation from WPV continues to expand, which this study fulfills.

3. Background

Currently, there are inconsistencies in the terminology used to distinguish between the types of energy resources used to generate electricity. From a resource economics perspective, energy resources used to generate electricity can be divided into two categories: fund resources and flow resources. Fund resources include energy resources that exist as a given, fixed stock, both in terms of quality and quantity (Bergstrom and Randall 2016, pgs. 30–37). Examples include fossil fuels (i.e., coal, oil, and natural gas).

Flow resources have unknown quality and quantity dimensions and can be either storable or non-storable (Bergstrom and Randall, pgs. 30–37). As their name suggests, storable flow resources used to generate electricity (which include hydropower and geothermal energy) can be captured and stored for future use, making them dispatchable (Nikoletatos and Tselepis 2015).[7] Conversely, non-storable flow resources used

[4] According to the U.S. Energy Information Administration (EIA) since 2007, WPV have continued as the second largest contributor to utility-scale capacity additions and currently account for nearly 10% of total generating capacity in United States (U.S. Energy Information Administration (EIA), 2017).

[5] The bulk power system (BPS) is a large interconnected electrical system made up of generation and transmission facilities and their control systems (NERC 2018).

[6] Burtraw et al. (2013) examine the impacts of the Cross-State Air Pollution Rule (CSAPR) and the Mercury and Air Toxins Standards (MATS) on electrical system reliability in the United States using the Haiku electricity market simulation model developed by Resources for the Future (RFF).

[7] The term energy storage can be used to describe technologies or devices that store energy for future use. Examples of energy storage devices include large-scale lithium-ion based batteries, pumped hydro storage, flywheel energy storage, compressed air storage, and solid mass gravitational storage. Because storage is not used on a large scale yet, when classifying energy resources used to produce electricity, system operators and utilities refer to resources as being either dispatchable or non-dispatchable. By their nature, all fund resources (both exhaustible and non-exhaustible) can be dispatched when and if they are needed, although at different ramp rates and associated costs.

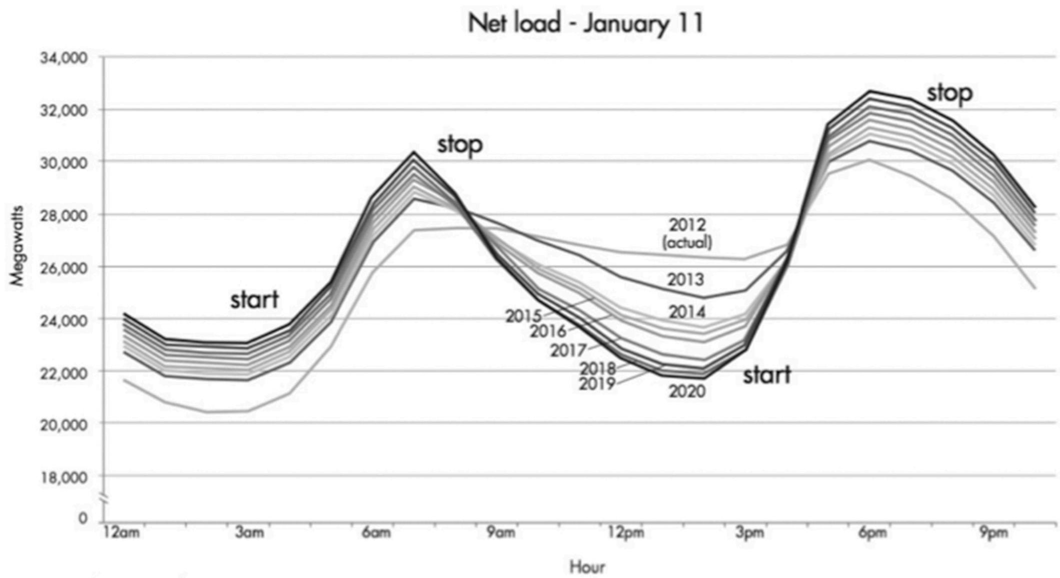

Fig. 1. California's duck curve: Over-generation of solar energy.
Source: California ISO (2016)

to generate electricity (which include WPV) cannot be stored for future use without large-scale batteries. Instead, their availability depends on real-time meteorological conditions, making them non-dispatchable.

To see the potential grid implications of the increased net generation from WPV, consider Fig. 1, which depicts California's load curve – otherwise known as the "duck curve" due to its shape.[8] The load curve in Fig. 1 illustrates the early-morning ramping period (approximately four to 6 a.m.), wherein the California Independent System Operator (ISO) must ensure an adequate amount of electricity is being generated to meet morning demand. Following the initial morning ramp, electricity demand declines rapidly as individuals leave home for work, school, or other obligations.

At this same time, the sun is coming up, allowing more solar to be brought online and conventional non-renewable generating resources to be ramped down. In the late afternoon-to-evening hours, as individuals begin to head home, generating capacity must ramp back up quickly to meet the increased demand. The sun, however, is starting to set, and solar is contributing less to power production. To meet this increase in demand, the system operator must re-ramp its non-renewable generation fleet.

According to the California ISO (2016), the curve illustrates three potential consequences of growing WPV penetration: ramping, oversupply, and decreased frequency response. As generation from WPV increases, the system operator must quickly bring on or shut down non-renewable generation to meet increasing or declining demand. Any fast ramp leads to a real risk of producing more electricity than is needed to meet the demand requirements, the management of which increases operating costs.[9]

As more renewable generators displace conventional generation, a loss of inertia occurs on a traditional power grid system (i.e., a system designed for electrons to flow from producer to end-consumer and not vice-versa). The mechanical energy produced from conventional fossil fuels is no longer the primary source of electricity being supplied. Instead, the power system now relies on variable energy resources, including WPV, whose mechanical energy output can fluctuate. The addition of WPV can cause the operator to lose the automated capability to manage frequency response. Consequently, the system becomes exposed to potential disruptions in generation or transmission outages, which following the traditional structure of the power grid system, can ultimately lead to disruptions for end-consumers.[10]

Given the availability of WPV depends directly on real-time meteorological conditions, it is difficult for the California ISO (or any system operator) to predict with absolute certainty the contribution the resources can make in real-time to overall capacity, especially during peak demand hours (Bird et al., 2013; Skea et al., 2008).[11] The variation in output from solar photovoltaics is generally more natural to model than wind, although cloud cover can make solar energy production far less predictable (Bird et al., 2013). That is, the variability in cloud cover can cause rapid changes in the output produced from installed solar panels (i.e., photovoltaic [P.V.] systems) (Bird et al., 2013).

4. Methodology

This section provides an overview of the data and empirical analysis techniques used to examine whether increasing the net generation of electricity supplied by WPV affects the duration or frequency of power system disruptions experienced by end-consumers.

[8] For more information on how utilities in California are enabling WPV to contribute to a larger share of their net generation, including an explanation of how generation from WPV is managed during times of insufficient demand visit the California Public Utilities Commission Website or the California Independent System Operator's (CAISO) website.

[9] It is worth noting that California ISO's operational decisions are driven, in part, by natural market processes. In other words, the near-zero marginal costs from renewable technologies are leading to a decline in wholesale electricity prices and affecting the operator's merit-order dispatch decisions (Prol et al., 2020).

[10] For more information see https://www.eia.gov/energyexplained/electricity/how-electricity-is-generated.php.

[11] Another issue that makes integrating more WPV onto the grid more difficult is that in its current state, electricity along the U.S. electrical grid only flows in one direction, from central generation to the end-consumer (Department of Energy 2015). As a result, any disruption that occurs at any point along the grid (e.g., during the generation, transmission, or distribution phases of production) can impact the ability of customers to receive an uninterrupted supply of power. For further clarification see Figure 7a. Three Phases of the Electricity Production Process in the list of figures at the end of the paper.

4.1. Data

To conduct our empirical analysis, data was collected from two annual surveys administered by the United States (EIA). Namely, survey Form EIA-923 and survey Form EIA-861. Survey Form EIA-923 provided yearly data on the operational characteristics of power-plants that supplied electricity to the grid between 2013 and 2017. Power plants were matched by *utility name* and *id* to observations in survey Form EIA-861, which provided information on the frequency and duration of power system disruptions experienced by end-consumers during each year, data on which has been collected by the EIA since 2013. Some utilities reported data for a varying number of years. As a result, our dataset existed as an unbalanced panel with 276 annual observations from 2013 to 2017. Summary statistics are presented in Table 1.

4.2. Measuring power system disruptions

The system average interruption duration index (*SAIDI*) reports the duration (usually measured in minutes) of power system disruptions experienced by end-consumers. The system average interruption frequency index (*SAIFI*) reports the frequency of disruptions (i.e., the number of times a customer has gone without power during the year).

Table 1
Panel summary statistics (2013–2017).

Variable	Description	Mean	Std. Dev.	Min	Max
SAIDI	System Average Interruption Duration Index	67.67	76.86	0	700.20
SAIFI	System Average Interruption Frequency Index	0.82	1.77	0	43.20
Customers	Number of Customers Served (Millions)	0.38	0.79	0	5.12
Auto	Indicator if Utility has an Automated Outage Management System	0.46	0.50	0	1
IEEE	Indicator for IEEE-1366 Standard	0.57	0.50	0	1
Circuits	Number of Distribution Circuits	427.73	712.71	1	4552
Sales	Total Electric Retail Sales (GWh)	9091.35	16,832.7	0	110,326.70
TR	Indicator = 1 if Utility Transmits Electricity	0.65	0.48	0	1
DR	Indicator = 1 if Utility Distributes Electricity	1.00	0.06	0	1
GR	Indicator = 1 if Utility Generates Electricity	0.91	0.30	0	1
FRCC	Indicator = 1 if Utility Identifies Florida Reliability Coordinating Council as NERC Region	0.06	0.23	0	1
HICC	Indicator = 1 if Utility Identifies Hawaiian Islands Coordinating Council as NERC Region	0.02	0.13	0	1
MRO	Indicator = 1 if Utility Identifies Midwest Reliability Organization as NERC Region	0.17	0.37	0	1
NPCC	Indicator = 1 if Utility Identifies Northeast Power Coordinating Council as NERC Region	0.07	0.26	0	1
RFC	Indicator = 1 if Utility Identifies Reliability First Corporation as NERC Region	0.15	0.36	0	1
SERC	Indicator = 1 if Utility Identifies Southeast Electricity Reliability Council as NERC Region	0.14	0.35	0	1
SPP	Indicator = 1 if Utility Identifies Southwest Power Pool as NERC Region	0.08	0.28	0	1
TRE	Indicator = 1 if Utility Identifies Texas Regional Entity as NERC Region	0.02	0.15	0	1
WECC	Indicator = 1 if Utility Identifies Western Electricity Coordinating Council as NERC Region	0.26	0.44	0	1
ASCC	Indicator = 1 if Utility Identifies Alaska Systems Coordinating Council as NERC Region	0.02	0.15	0	1
Cooperative	Indicator = 1 if Utility is Owned by a Cooperative as NERC Region	0.07	0.25	0	1
Investor	Indicator = 1 if Utility is Investor Owned	0.37	0.48	0	1
Municipal	Indicator = 1if Utility is Owned by Municipality	0.48	0.50	0	1
Subdivision	Indicator = 1 if Utility Owned by a Subdivision	0.08	0.27	0	1
State	Indicator = 1 if Utility is State Owned	0.004	0.06	0	1
Net Generation	Net Generation (GWh)	7237.10	15,639.06	−113.06	115,648.60
WPV	Net Generation (GWh) supplied by Wind and Solar Photovoltaics	98.93	646.38	0	11,680.17
WPV^2	Net Generation (GWh) supplied by Wind and Solar Photovoltaics Squared	427,169.30	5,894,633	0	13,600,000,000
WPV Prime	Indicator Utility has at Least one Wind or Solar as Prime Mover	0.23	0.42	0	1
Instrumental Variables (Annual)					
RPS Requirement	Requirement (%) to meet Renewable Portfolio Standard	6.83	8.80	0	55
REPTC	Potential Compensation (USD) from Renewable Electricity Production Tax Credit	2,276,733	1,490,000,000	0	27,300,000,000

Table 2
First Stage OLS Estimates. Dependent variables WPV_{it} and. WPV_{it}^2

Dependent Variable	WPV_{it}		WPV_{it}^2
Excluded Instruments			
RPS percent requirement	0.1610*	RPS percent requirement sq.	1.163
	(0.009)		(1.677)
Qualifying amount REPTC ($)	4.35×10^{-5}***	Qualifying amount REPTC ($) sq.	1.91×10^{-9}***
	5.82×10^{-8}		2.56×10^{-11}
Other Exogenous Variables			
WPV Prime Mover	−0.1171	WPV Prime Mover	743.93
	(0.4341)		(765.53)
Customers	−0.4061	Customers	−507.99
	(0.3436)		(632.45)
IEEE	0.1802	IEEE	63.21
	(0.1200)		(273.86)
Circuits	0.0007	Circuits	0.8127
	(0.0004)		(0.7001)
GR	−0.0863	GR	−164.11
	(0.1452)		(334.44)
Constant	−0.3307	RPS percent requirement	2.4272
	(0.3685)		
		Qualifying amount REPTC ($)	−0.0005
			(0.0007)
		Constant	−207.25
			(974.15)
Observations	924	Observations	924
R^2	0.9997	R^2	0.9997

Notes: (i) Standard errors in parenthesis. (ii) The asterisk symbols represent the following: *p < 0.10, ** p < 0.05, *** p < 0.01. (iii) Parameter estimates not included in results: the total amount of retail sales (GWhs), an indicator for transmission, an indicator for distribution, and an indicator for automatic detection for system disruptions. (iv) Year, NERC Region, and Ownership fixed effects are included in both models.

Table 3
F-Test Results for Hypothesis that Utility-Level Specific Effects have No Effect on Duration and Frequency of Disruptions in Power Reliability.

Reliability Metric	*F*-test	Degrees of Freedom (between/within)	Prob. > *F*
ln(SAIDI)	7.90	(247/661)	<0.000
ln(SAIFI)	7.09	(247/661)	<0.000
arsinh(SAIDI)	9.06	(247/661)	<0.000
arsinh(SAIFI)	7.20	(247/661)	<0.000

Notes: The representation for the natural logarithmic and inverse hyperbolic sine functions are ln(•) and arsinh(•), respectively.

SAIDI and *SAIFI* were developed by the Institute of Electrical and Electronics Engineers (IEEE) (1998). The two indices are said to provide a consistent approach for utilities interested in measuring the reliability of their electricity distribution system (Eto et al., 2012; Malla 2013).

SAIDI is calculated as follows

$$SAIDI = \sum\nolimits_{i=1}^{n}(d_i * N_i) \Big/ N_t . \quad (1)$$

In Eq. (1) d_i is used to represent the restoration time (i.e., the amount of time it takes for power to be restored to the customer) in minutes; N_i is used to denote the number of customers who experienced the power system disruption; and N_t is used to represent the total number of customers served by an individual utility during time period t.

SAIFI is calculated as follows:

$$SAIFI = \sum\nolimits_{i=1}^{n} N_i \Big/ N_t . \quad (2)$$

N_i and N_t in Eq. (2) are defined the same as in Eq. (1). By design, larger values of *SAIDI* and *SAIFI* indicate less reliable electricity distribution service (i.e., more prolonged and more frequent disruptions have occurred) and lower values of *SAIDI* and *SAIFI* represent more reliable electricity distribution service.[12]

Following Eto et al. (2012) and Malla (2013), we separated disruptions that occurred during major event days (MEDs) from disruptions that did not happen during MEDs.[13] Because we were interested in understanding the impact of using WPV on reliability, our analysis only considered values for *SAIDI* and *SAIFI* recorded on non-MEDs.

4.3. Empirical analysis

Our empirical analysis followed four main steps. First, consistent with Eto et al. (2012), we transformed both indices (*SAIDI* and *SAIFI*) using a log-transformation. Also, we employed an inverse hyperbolic

[12] Values for *SAIDI* and *SAIFI* reported on survey form EIA-861 from 2013 to 2017 are presented in the online appendix. See Figs. 1a and 2a.

[13] A major event day (MED) is defined as a day where a power system interruption is likely the result of a severe weather-related event (e.g., a lightning strike, snowstorm, ice storm, hurricane, tornado, or flood). Values for *SAIDI* and *SAIFI* are likely to be inflated on MED. Eto et al. (2012) and Malla (2013) both argue that failure to separate power system disruptions that occur during MED from outages that occur on non-MED could degrade the comparability of the indices across different utilities because depending on which region the electric utility operates in; they could naturally be more prone to experiencing major weather events. For example, utilities that operate along the coast are inherently more prone to hurricanes than those who operate inland.

Table 4
Random effects model results for duration and frequency of power disruptions experienced.

	ln(*SAIDI*)	ln(*SAIFI*)	arsinh(*SAIDI*)	arsinh(*SAIFI*)	ln(*SAIDI*)	ln(*SAIFI*)	arsinh(*SAIDI*)	arsinh(*SAIFI*)
WPV	0.0009***	0.0002	0.0009***	0.0002**	0.0009***	0.0002	0.0009***	0.0002*
	(0.0003)	(0.0002)	(0.0003)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0001)
WPV^2	-3.60×10^{-7}**	-1.16×10^{-7}	-3.50×10^{-7}**	-1.18×10^{-7}***	-3.57×10^{-7}**	-1.09×10^{-7}	-3.46×10^{-7}**	-1.13×10^{-7}**
	(1.51×10^{-7})	(8.17×10^{-7})	(1.52×10^{-7})	(5.43×10^{-8})	(1.52×10^{-7})	(8.12×10^{-7})	(1.53×10^{-7})	(5.42×10^{-7})
WPV Prime	−0.3435***	−0.0586	−0.3551***	−0.1133***	−0.3421***	−0.0582	−0.3537***	−0.1131***
	(0.1156)	(0.0778)	(0.1233)	(0.0388)	(0.1154)	(0.0778)	(0.1232)	0.0388
Customers	−0.4805**	−0.3085	−0.4642**	−0.1700***	−0.4813**	−0.3085	−0.4650**	−0.1700**
	(0.1986)	(0.2006)	(0.2126)	(0.0862)	(0.1988)	(0.2006)	(0.2128)	(0.0862)
IEEE	1.2550***	−0.1743*	1.4095***	0.2630***	1.2550***	−0.1743*	1.4095***	0.2629***
	(0.2022)	(0.0971)	(0.2128)	(0.0430)	(0.2022)	(0.0972)	(0.2128)	(0.0430)
Circuits	0.0004**	0.0001	0.0005*	0.0001	0.0004**	0.0001	0.0005*	0.0001
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
GR	−0.2909	0.3182**	−0.3237	0.0124	−0.2909	0.3182**	−0.3237	0.0125
	(0.1955)	(0.1508)	(0.2188)	(0.0509)	(0.1955)	(0.1508)	(0.2188)	(0.0509)
Constant	5.2183***	0.4628**	5.8395***	1.1422***	5.2174***	0.4629**	5.8387***	1.1422***
	(0.5804)	(0.2434)	(0.6509)	(0.1653)	(0.5804)	(0.2434)	(0.6509)	(0.1653)
NERC Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Observations	924	924	924	924	924	924	924	924
Hausman test (m-value)	8.36	18.87	8.71	11.32	8.39	18.86	8.73	11.32
Hausman $\chi^2(13)$	0.820	0.127	0.798	0.584	0.817	0.128	0.793	0.5838
IV Diagnostics								
First stage F-Test of excluded instruments (F-stat, p-value)					0.00			
Under identification (Kleibergen-Papp rank LM F-stat, p-value)					0.00			
Over-identification (Hansen's J, p-value)					0.52			
Weak identification (Cragg-Donald Wald Test F-stat)					1.50×10^5			
Stock-Yogo critical value: 10% max					19.93			
Stock-Yogo critical value: 15% max					11.59			
First stage F-Test of excluded instruments (F-stat, p-value)					0.00			

Notes: (i) Standard errors in parenthesis. (ii) The asterisk symbols represent the following: *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (iii) Parameter estimates not included in results: the total amount of retail sales (GWhs), an indicator for transmission, an indicator for distribution, and an indicator for automatic detection for system disruptions. (iv) *SAIDI* denotes system average interruption duration index; *SAIFI* denotes system average interruption frequency index. (v) IV.

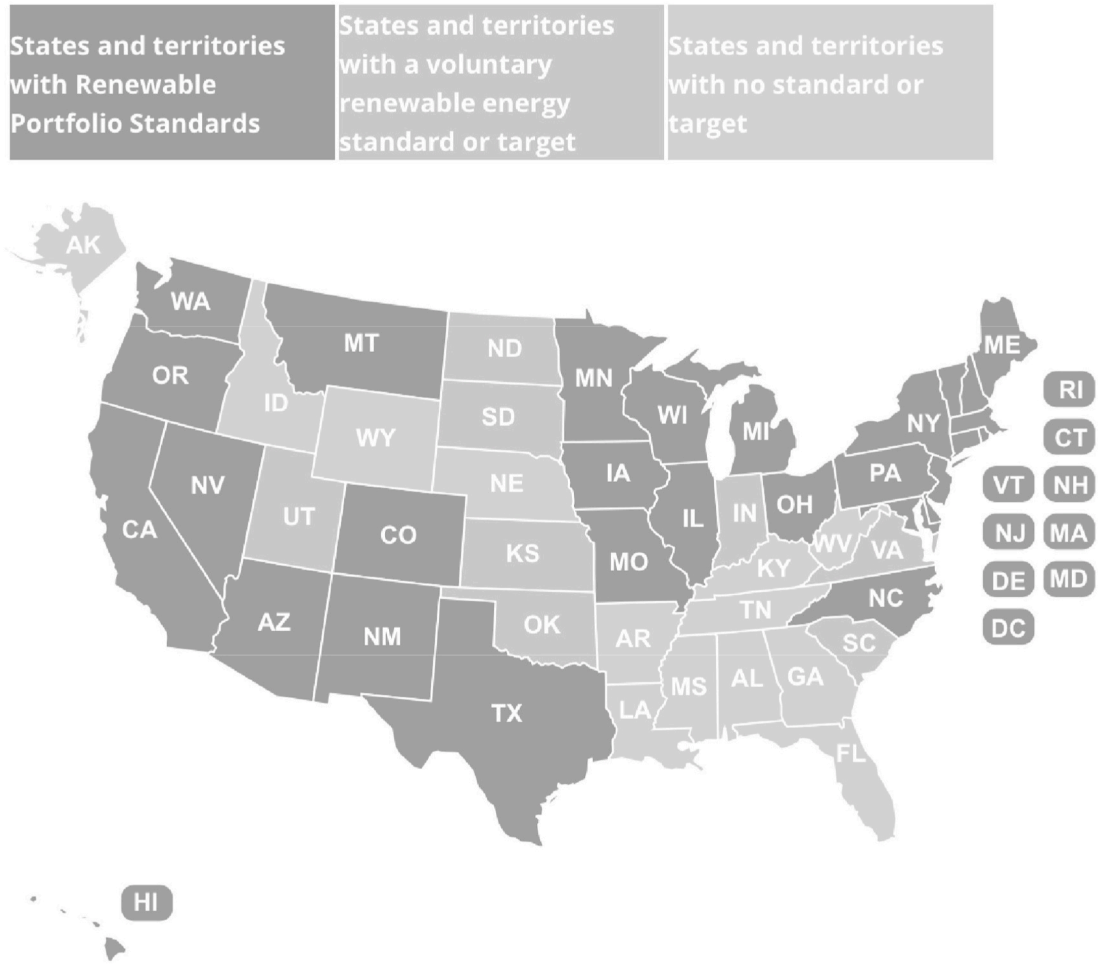

Fig. 2. States with and without active renewable support policies in place.
Source: National Conference of State Legislatures (2019).

sine (IHS) transformation of the two indices (Johnson, 1949).[14][15] Second, we conducted *F*-tests on both transformed values of *SAIDI* and *SAIFI* to determine if accounting for utility-specific effects was warranted. Third, we conducted a Hausman (1978) specification test to determine whether a fixed or random-effects model approach was more appropriate. Fourth, we estimated two sets of models using the transformed values of *SAIDI* and *SAIFI* as the dependent variable.

The reduced-form model used to test our hypothesis takes the following form:

$$Disruption_{it} = \beta_0 + \beta_1 WPV_{it} + \beta_2 WPV_{it}^2 + \beta_3 WPVPrime_{it} + \boldsymbol{\delta X_{it}} + \gamma Year_{t-1} + c_i + \mu_{it}. \tag{3}$$

The dependent variable in Eq. (3), $Disruption_{it}$, is a positive, continuous variable equal to the natural log or the IHS transformed values of *SAIDI* or *SAIFI*. Our primary variables of interest are WPV_{it} and WPV_{it}^2 continuous variables equal to the amount of net generation supplied by WPV (measured in GWhs) by each utility *i* in each time period *t* and its square.[16] The variable WPV_{it}^2 is included to capture the potential diminishing marginal effect of net generation supplied by WPV on the frequency or duration of power system disruptions experienced.

As utilities supply more net generation from WPV, it is plausible that they may become better equipped to manage power system disruptions resulting from their use. Therefore, we hypothesized the estimated coefficient for $\beta_2$will be negative. Following, this same logic we hypothesized initial increases the amount of net generation from WPV would lead to an increase in the frequency and duration of disruptions experienced; hence, we expected a positive sign for the estimated coefficient, β_1. As a robustness check, we also include a variable labeled as $WPVPrime_{it}$ which is a binary indicator variable if a utility company

[14] While the log-transformation is convenient, applying such a transformation can lead to negative values for *SAIDI* and *SAIFI* being recorded, which is problematic as the negative of a power system disruption is nonsensical. Furthermore, given values of *SAIDI* and *SAIFI* are skewed to the right and a large number of utilities recorded values of *SAIDI* and *SAIFI* equal to zero across various years, we apply the IHS transformation to values for *SAIDI* and *SAIFI*. The IHS transformation is defined at zero, corrects for skewness, and is approximately equal to $\log(2y_{it})$ or $\log(2) + \log(y_{it})$. As a result, parameters of interest can still be interpreted as the percentage change in a reliability index, given a one-unit change in a variable of interest.

[15] Fig. 3a through 6a in the online appendix show the results of the data transformations applied.

[16] Generation from WPV excludes generation supplied to utilities through net metering programs.

Table 5
Predicted frequency of disruptions *(SAIFI)* based on results from the random effects IV regression.

States with Renewable Portfolio Standards (RPS)		% of Net Generation Projected to be Supplied By WPV					
		5%	10%	25%	50%	75%	100%
Arizona	AZ	1.82	0.63	0.53	0.53	0.53	0.53
California	CA	1.82	1.80	1.73	1.57	1.43	1.35
Colorado	CO	2.27	2.10	1.46	1.29	1.06	0.86
Connecticut	CT	2.28	2.28	2.28	2.28	2.28	2.28
Delaware	DE	2.58	2.58	2.58	2.58	2.58	2.58
Hawaii	HI	3.07	3.11	3.19	3.17	2.99	2.76
Illinois	IL	2.20	2.21	2.23	2.24	2.22	2.16
Iowa	IA	1.97	1.80	1.42	1.27	1.21	1.21
Maine	ME	3.33	3.33	3.33	3.33	3.33	3.33
Maryland	MD	1.36	1.36	1.36	1.36	1.36	1.36
Massachusetts	MA	2.07	2.07	2.07	2.07	2.08	2.08
Michigan	MI	2.13	1.94	1.66	1.58	1.59	1.59
Minnesota	MN	1.63	1.57	1.46	1.37	1.33	1.33
Missouri	MO	2.23	1.99	1.67	1.52	1.47	1.40
Nevada	NV	2.78	2.76	1.88	1.00	0.46	0.15
New Hampshire	NH	3.20	3.26	3.39	3.49	3.42	3.21
New Jersey	NJ	2.36	2.36	2.36	2.37	2.38	2.39
New Mexico	NM	1.92	1.93	1.69	1.39	1.38	1.40
New York	NY	2.39	2.40	2.43	2.43	2.38	2.29
North Carolina	NC	2.08	0.87	0.69	0.69	0.69	0.69
Ohio	OH	1.85	1.84	1.66	1.53	1.52	1.52
Oregon	OR	2.25	2.28	2.17	1.82	1.70	1.65
Pennsylvania	PA	1.82	1.82	1.82	1.82	1.82	1.82
Texas	TX	2.16	2.16	1.78	1.32	1.10	0.96
Vermont	VT	2.00	2.00	2.02	2.04	2.06	2.08
Virginia	VA	1.86	1.58	1.57	1.57	1.57	1.57
Washington	WA	1.98	2.02	1.98	1.67	1.46	1.37
Wisconsin	WI	2.20	2.15	1.70	1.24	1.08	1.03
States with Renewable Portfolio Goals (RPG)		**% of Net Generation Projected to be Supplied By WPV**					
		5%	**10%**	**25%**	**50%**	**75%**	**100%**
Indiana	IN	2.23	2.08	1.31	0.79	0.69	0.63
Kansas	KS	2.31	2.30	2.01	1.83	1.83	1.82
North Dakota	ND	1.65	1.66	1.69	1.74	1.78	1.80
Oklahoma	OK	2.39	2.24	1.49	0.92	0.66	0.54
South Carolina	SC	2.65	2.34	0.54	0.18	0.18	0.18
South Dakota	SD	2.42	2.42	2.43	2.44	2.45	2.46
Utah	UT	1.73	1.73	1.74	1.74	1.74	1.74

Note: (i) Predicted values of *SAIFI* were note estimated for Montana or Rhode Island. Data on these two states were not provided on Survey Form EIA-861 or 923.

Table 6
Predicted duration of disruptions *(SAIDI)* based on results from the random effects IV regression.

States with Renewable Portfolio Standards (RPS)		% of Net Generation Projected to be Supplied By WPV					
		5%	10%	25%	50%	75%	100%
Arizona	AZ	191	36	36	36	36	36
California	CA	268	267	266	189	162	139
Colorado	CO	579	436	235	212	170	157
Connecticut	CT	133	133	133	134	134	135
Delaware	DE	684	684	684	685	686	687
Hawaii	HI	303	328	387	388	298	226
Illinois	IL	339	340	343	346	345	341
Iowa	IA	624	321	91	74	74	76
Maine	ME	822	822	822	822	822	822
Maryland	MD	22	22	22	22	22	22
Massachusetts	MA	128	128	128	128	128	128
Michigan	MI	437	311	227	224	229	234
Minnesota	MN	152	129	112	86	86	88
Missouri	MO	527	309	171	156	136	110
Nevada	NV	1086	1168	700	299	47	3
New Hampshire	NH	636	680	804	948	972	876
New Jersey	NJ	595	596	601	609	617	625
New Mexico	NM	301	329	160	106	112	118
New York	NY	280	286	301	311	303	290
North Carolina	NC	482	27	26	26	26	26
Ohio	OH	252	255	186	173	176	176
Oregon	OR	513	560	512	431	431	427
Pennsylvania	PA	103	103	103	104	104	104
Texas	TX	439	487	334	180	113	70
Vermont	VT	59	60	63	67	71	74
Virginia	VA	155	133	133	134	134	134
Washington	WA	258	283	296	228	216	209
Wisconsin	WI	525	536	403	164	105	96
States with Renewable Portfolio Goals (RPG)		**% of Net Generation Projected to be Supplied By WPV**					
		5%	**10%**	**25%**	**50%**	**75%**	**100%**
Indiana	IN	519	425	124	35	23	15
Kansas	KS	503	514	358	359	376	388
North Dakota	ND	77	80	87	98	107	115
Oklahoma	OK	540	568	419	147	45	15
South Carolina	SC	906	709	9	4	4	4
South Dakota	SD	615	617	621	627	633	640
Utah	UT	131	131	132	132	132	133

Note: (i) Predicted values of *SAIDI* were note estimated for Montana or Rhode Island. Data on these two states were not provided on Survey Form EIA-861 or 923.

identified either wind or solar photovoltaics as a prime mover for at least one of the generating plants it used to supply electricity.[17]

We control for year fixed effects by including the variable $Year_{t-1}$, which represents a set of year indicator variables for all but one of the five years of observation. The term c_i denotes the unobserved individualutility-level effects believed to influence disruptions in the reliability of service. The idiosyncratic error term is represented in Eq. (3) by μ_{it}. The term X_{it} represents a vector of operational characteristics that influence the frequency and duration of power system disruptions experienced by end-consumers.

Control variables in X_{it} included: $Auto_{it}$, a binary indicator variable if the electric utility had an outage management system capable of automatically detecting disruptions; TR_{it}, a binary indicator variable if the utility transmits electricity; and DR_{it}, a binary indicator variable if the utility operates its own distribution lines. Further, we control for: GT_{it}, a binary indicator variable if the utility generates its own electricity, $Circuits_{it}$, a continuous variable equal to the number of distributional circuits operated by each utility i in time period t; and, $Sales_{it}$, total annual retail sales for each utility (measured in gigawatt-hours [GWh]). Finally, the term $IEEE_{it}$ denotes a binary indicator variable if the utility uses the IEEE Standard 1366 to record and measure values for *SAIDI* and *SAIFI*.[18]

Consistent with the previous literature, we control for the size of each utility by including a variable equal to the total number of

[17] A prime mover is the engine, turbine, water wheel, or other similar machine responsible for driving the electric generator in a power plant; or, for reporting purposes, the device that converts energy to electricity directly. Including an indicator variable for prime mover identified as wind or solar, allows us to further investigate how small increases in net capacity being supplied by WPV might differ from large increases. It also provides some evidence that utilities who have one prime mover of wind or solar may have additional units of other resources, that could potentially be used for back-up generation (U.S. Energy Information Administration (EIA), 2019b).

[18] While *SAIDI* and *SAIFI* are both widely recognized metrics used to measure power system reliability, there are differences among the ways utilities define and measure interruptions using these two indices (Eto at al. 2012; Malla 2013). For example, some follow the IEEE 1366 Standard to measure values for *SAIDI* and *SAIFI*, while others use their own set of criteria to measure disruptions using the indices. To control for the differences in criteria used to record and measure outages we include the indicator variable *IEEE*.

Table 7
Estimated # of residential and non-residential customers in states with renewable energy support policies in place.

State		Average # Of Customers	Proportion of Customers in Groups		Estimated # of Customers in Groups	
			Residential	Non-Residential	Residential	Non-Residential
States with Renewable Portfolio Standards (RPS)						
Arizona	AZ	713,960	89%	11%	637,575	76,385
California	CA	935,728	88%	12%	822,663	113,065
Colorado	CO	588,747	85%	15%	502,696	86,050
Connecticut	CT	120,314	90%	10%	108,715	11,599
Delaware	DE	88,484	89%	11%	78,326	10,158
Hawaii	HI	128,238	87%	13%	112,121	16,117
Iowa	IA	158,573	85%	15%	134,543	24,030
Illinois	IL	28,695	89%	11%	25,676	3,019
Massachusetts	MA	15,848	87%	13%	13,763	2,085
Maryland	MD	10,587	90%	10%	9,502	1,086
Maine	ME	152,747	88%	12%	134,063	18,685
Michigan	MI	479,555	89%	11%	425,957	53,598
Minnesota	MN	105,326	89%	11%	93,555	11,771
Missouri	MO	201,657	88%	12%	176,805	24,851
North Carolina	NC	961,518	87%	13%	832,539	128,979
New Hampshire	NH	509,502	85%	15%	431,889	77,613
New Jersey	NJ	2,283,110	87%	13%	1,987,408	295,702
New Mexico	NM	140,691	85%	15%	120,019	20,671
Nevada	NV	623,802	87%	13%	545,803	77,999
New York	NY	1,040,117	87%	13%	903,796	136,321
Ohio	OH	283,247	88%	12%	250,519	32,728
Oregon	OR	377,555	87%	13%	327,802	49,753
Pennsylvania	PA	11,250	88%	12%	9,913	1,338
Texas	TX	291,659	87%	13%	253,832	37,827
Virginia	VA	519,294	89%	11%	460,082	59,212
Vermont	VT	82,049	89%	11%	72,693	9,355
Washington	WA	243,623	85%	15%	207,583	36,040
Wisconsin	WI	336,104	88%	12%	296,375	39,729
States with Renewable Portfolio Goals (RPG)						
Indiana	IN	311,437	88%	12%	275,311	36,127
Kansas	KS	149,755	83%	17%	124,291	25,464
North Dakota	ND	88,992	82%	18%	73,257	15,734
Oklahoma	OK	467,715	85%	15%	399,268	68,447
South Carolina	SC	414,662	86%	14%	355,588	59,074
South Dakota	SD	65,717	84%	16%	55,208	10,509
Utah	UT	19,496	89%	11%	17,280	2,216

Note: Data collected from Survey Form EIA-861.

customers (measured in millions) each utility serves in X_{it}, labeled as $Customers_{it}$(Fenrick and Getachew 2012; Malla 2013).[19] To account for differences in the way reliability standards are monitored and enforced, we include a set of indicator variables for all but one of the ten North American Electrical Reliability (NERC) regions that utilities could report having operated in, labeled in our analysis as $NERC_{it}$. To account for the different procedures used by different types of utilities to manage their operations, we also include an indicator variable for each ownership type excluding one, labeled as $ownership_{it}$.[20]

4.4. Instrumental variables approach

If increasing the amount of net generation supplied by WPV is known to lead to longer or more frequent power system disruptions, then utilities may be less likely to install WPV to supply their electricity needs. Given the potential endogenous relationship between the amount of net generation supplied by WPV and the frequency or duration of power system disruptions experienced, we employed an instrumental variables (IV) approach to estimate Eq. (3). For our IV approach to be valid, the identified instruments must meet the following two conditions. One, identified instruments must be excludable in the sense that they have no direct effect on the outcome variable of interest. Two, identified instruments must be correlated with the endogenous variable for which they are instrumenting (Wooldridge 2010).[21]

Following Johnson and Oliver (2019), we utilize various aspects of a state's policy support for generation from renewable energy resources as our primary choice of instrumentation. In an attempt to combat greenhouse gas emissions from traditional fossil fuel resources, several states across the U.S. have implemented economic support policies to stimulate investment in renewable energy resources (Johnson and Oliver

[19] According to Fenrick and Getachew (2012) and Malla (2013) utilities serving fewer customers can be at a disadvantage when measuring the reliability of service using *SAIDI* and *SAIFI* values because they have fewer customers overall.

[20] For a graphical representation of the different NERC regions see Fig. 9a North American Reliability Council (NERC) Regions. The NERC is a not-for-profit international regulatory authority whose mission is to assure the effective and efficient reduction of risks to the reliability and security of the grid. NERC develops and enforces reliability standards and annually assesses seasonal and long-term reliability. NERC delegates its authority to monitor and enforce compliance to different regional entities. Each regional entity follows its own set of standards to monitor and enforce reliability. Ownership categories include investor owned, publicly owned (state and political subdivision) and cooperatives. Investor owned utilities are large electric distributors that issue stock owned by shareholders. Publicly owned utilities are utilities that residents vote into existence that operate independently. Cooperative are not-for-profit utilities. For more information see (U.S. Energy Information Administration (EIA), 2019c).

[21] Because the first condition involves examining the covariance between potential instruments and the unobserved error term, we cannot test whether or not it holds (Wooldridge 2010). By contrast, condition (2) can be tested by regressing the endogenous variable WPV_{it}on the identified instruments and all other exogenous variables included in the model and then examining whether the coefficient on the candidate instrument is non-zero.

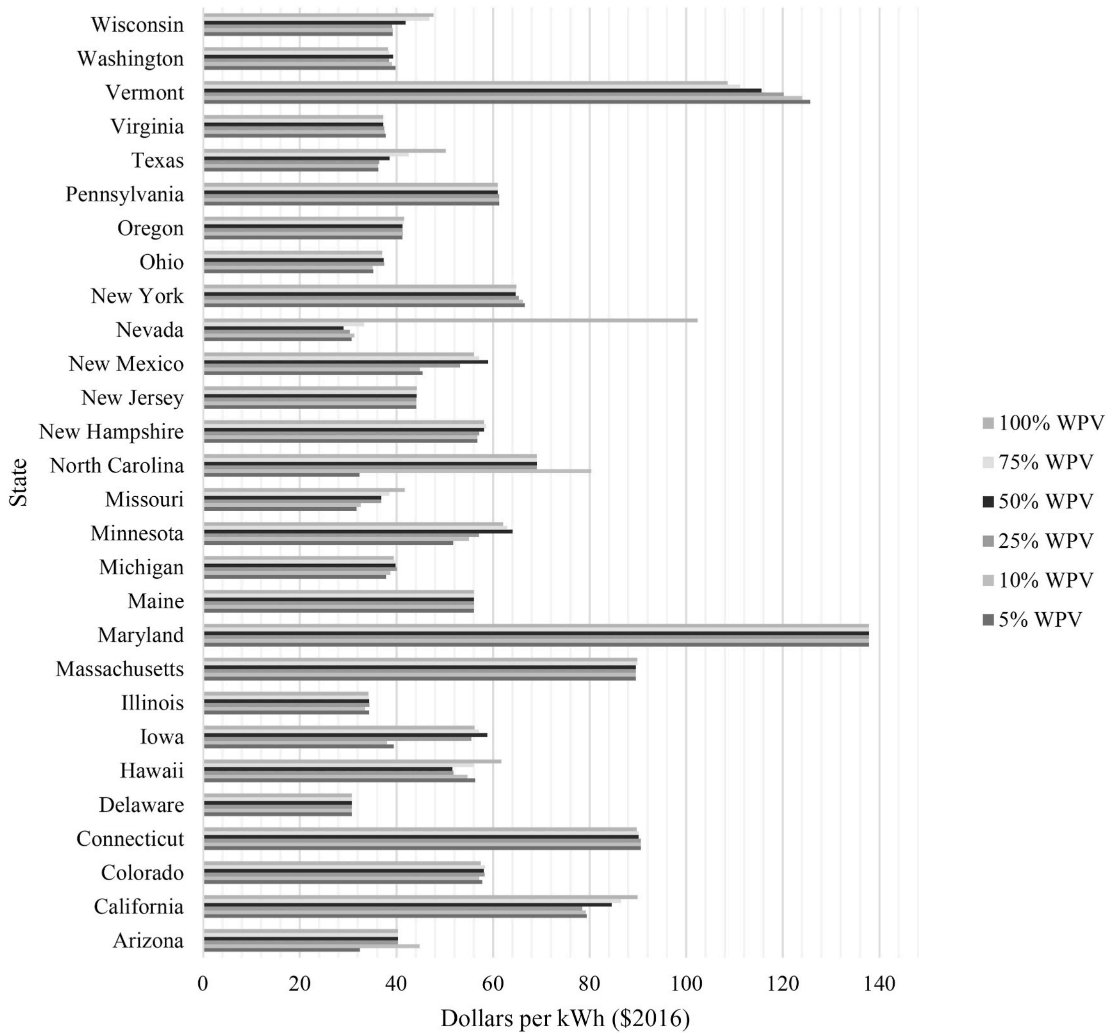

Fig. 3. Cost per unserved kWh of electricity derived from the ICE Calculator ($2016) for states with active Renewable Portfolio Standard (RPS).

2019). Perhaps the two most common include renewable portfolio standards (RPS) and the Renewable Electricity Production Tax Credit (REPTC).

RPS, represented by the covariate RPS_{it} are state-level regulatory mandates requiring a minimum amount of electricity be generated from renewable energy resources (Barbose 2017).[22] Electric utilities can meet RPS requirements by operating their renewable generating unit or purchasing renewable generation from other facilities (Johnson and Oliver 2019; Wiser et al., 2005). State-level data on annual RPS requirements were collected from the Lawrence Berkley National Laboratory (Barbose 2017). Following Johnson and Oliver (2019) we expect the relationship between the yearly RPS requirement and WPV_{it} to be positive.

The REPTC, represented by $REPTC_{it}$, is a per kilowatt-hour (kWh) tax credit for electricity produced using qualified energy resources, including WPV (Sherlock 2020). The maximum credit is set at 1.5 cents per kWh produced and is adjusted for inflation annually using the inflation adjustment factor published by the Internal Revenue Service (IRS). Our preferred instrumentation utilizes the amount of the Renewable Electricity PTC ($USD) a utility qualifies for based on the amount of net generation from WPV they supply in a given year. We expect the relationship between the qualifying Renewable Electricity PTC and WPV_{it} to also be positive.

Our first-stage estimating equation is as follows:

$$WPV_{it} = \pi_0 + \pi_1 \boldsymbol{Z}_{it} + \eta \boldsymbol{X}_{it} + \rho Year_{t-1} + \omega_i + \varepsilon_{it}, \tag{4}$$

where in Eq. (4) $\boldsymbol{Z}_{it}$ is the vector of instrumental variables, $\boldsymbol{X}_{it}$ is a vector of exogenous variables from Eq. (3), ω_i represents individual utility-level effects, $Year_{t-1}$ are the year fixed effects, and ε_{it} is the idiosyncratic error term. We control for the potential endogeneity between WPV^2_{it} and the frequency or duration of power system disruptions experienced following suggestions Wooldridge (2010). Instruments include RPS^2_{it} and $REPTC^2_{it}$. The first-stage estimating equation for WPV^2_{it} is identical to the first stage estimating equation represented in Eq. (4) except the vector of instrumental variables now include both $\boldsymbol{Z}_{it}$ and. $\boldsymbol{Z}^2_{it}$.

Table 2 presents the first-stage OLS estimates for WPV_{it} and WPV^2_{it}.

Our chosen instruments explain the variation in WPV_{it} quite robustly. The estimate for the coefficient on RPS_{it} is positive and statistically significant. The interpretation of this coefficient estimate is that a one percent increase in an RPS requirement leads to a 0.16 percentage point increase in net generation from WPV. The estimates for the coefficients on RPS^2_{it} and $REPTC^2_{it}$ are both positive, as expected. However only the coefficient estimate on $REPTC^2_{it}$ is statistically significant. As we only have one endogenous variable, the rank and order conditions are still satisfied.

[22] For example, a RPS might require utilities to increase the amount of electricity the generate from renewables by 1% a year for the next ten years, resulting in a cumulative 10% increase in renewable generation in that state.

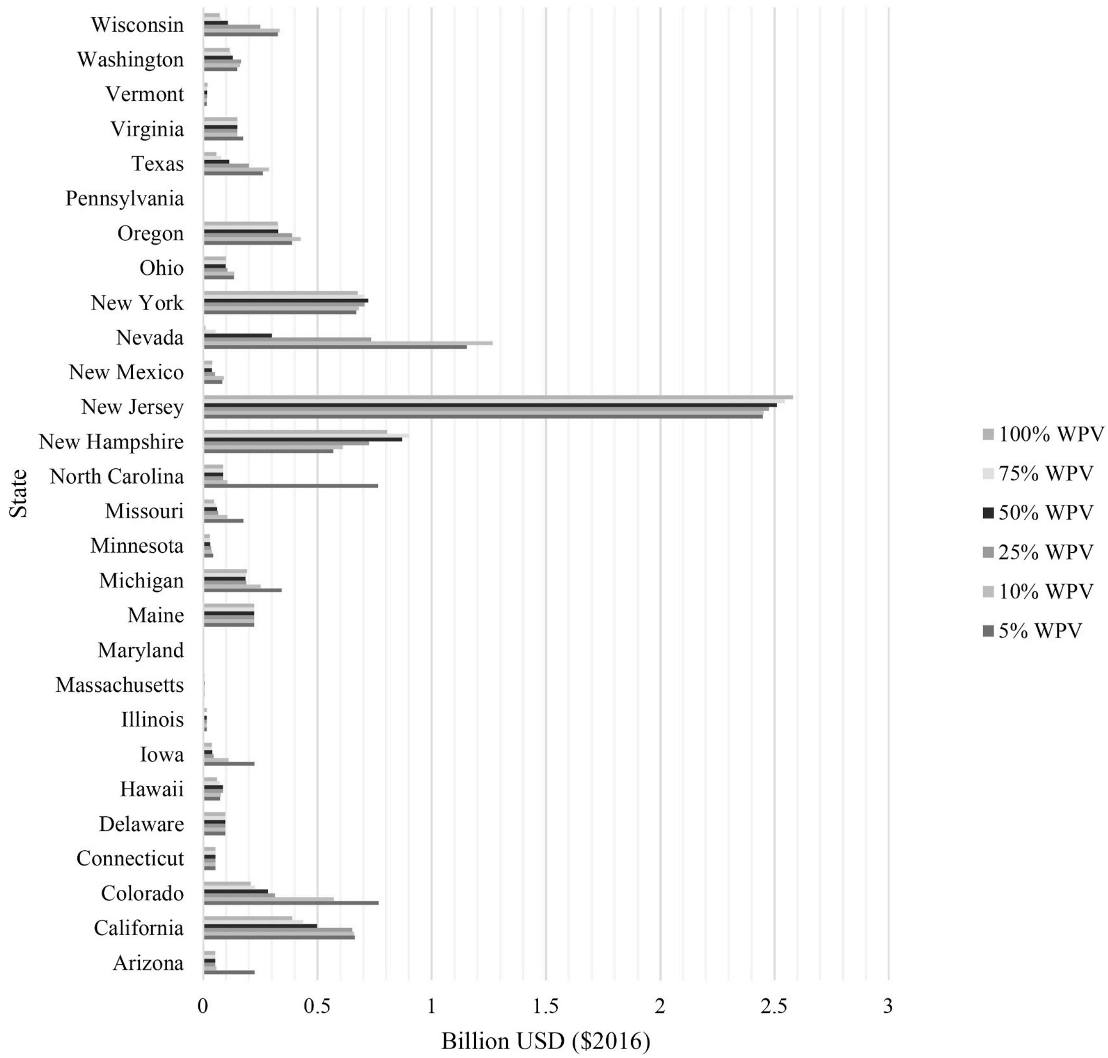

Fig. 4. Total costs of sustained power system interruptions ($2016) for states with active Renewable Portfolio Standard (RPS).

5. Main results and discussion

The results from the application of the *F*-test are presented in Table 3. Our findings suggest that both utility and year-specific effects are statistically significant (at the 0.01% confidence level) for both the log-transformed and IHS transformed values of *SAIDI* and *SAIFI.* The *F*-test result implies a strong correlation between the individual characteristics of the utilities and the value of the reliability indices recorded. Similar to Eto et al. (2012), we assumed this correlation is due to differences in reporting and monitoring practices of the individual utilities.[23]

The conventional technique used when analyzing short, unbalanced ($T_i \neq T$ for some i) panel datasets is to rely on multivariate regression models that account for unobserved heterogeneity (Cameron and Trivedi 2009; Wooldridge 2010). Options include fixed or random effects, the choice between which depends on assumptions surrounding the correlation between the individual unobserved effects (heterogeneity) and included explanatory variables of interest and whether any time-invariant explanatory variables are of interest to the researcher.[24]

In our specific case, time-invariant explanatory variables of interest include the NERC region each utility operates in and its ownership type. The results of the Hausman specification test indicated a violation of the assumption of no correlation between the unobserved, heterogeneous effects, and the NERC region (Wooldridge 2010). Thus, we estimated our empirical model Eq. (3) using a random-effects approach with standard errors corrected for both heteroscedasticity and autocorrelation.[25] We estimated the model with and without controlling for the potential endogeneity. The results are presented in Table 4.[26]

[23] It is important to take this correlation into account when examining the relationship between reported reliability indices and other explanatory variables of interest, as the way in which utilities record values for the disruptions experienced by their end-consumers could be similar to other reporting and monitoring strategies used by the utility. Controlling for this unobserved heterogeneity can help to eliminate the potential for bias in results.

[24] Fixed effects models are often preferred as the empirical approach when analyzing panel data as they allow for correlation between unobserved, heterogeneous effects, and any included explanatory variables of interest. However, if unobserved effects are not correlated with included explanatory variables of interest, random effects models are more appropriate.

[25] Regional reliability organizations are charged with monitoring and enforcing reliability standards. Being able to estimate the impact of operations of these organizations on reliability of service is an advantage of the random effects model specification as compared to the fixed effects model.

[26] Additional robustness checks can be found in Tables 1a-5a in the supplementary material

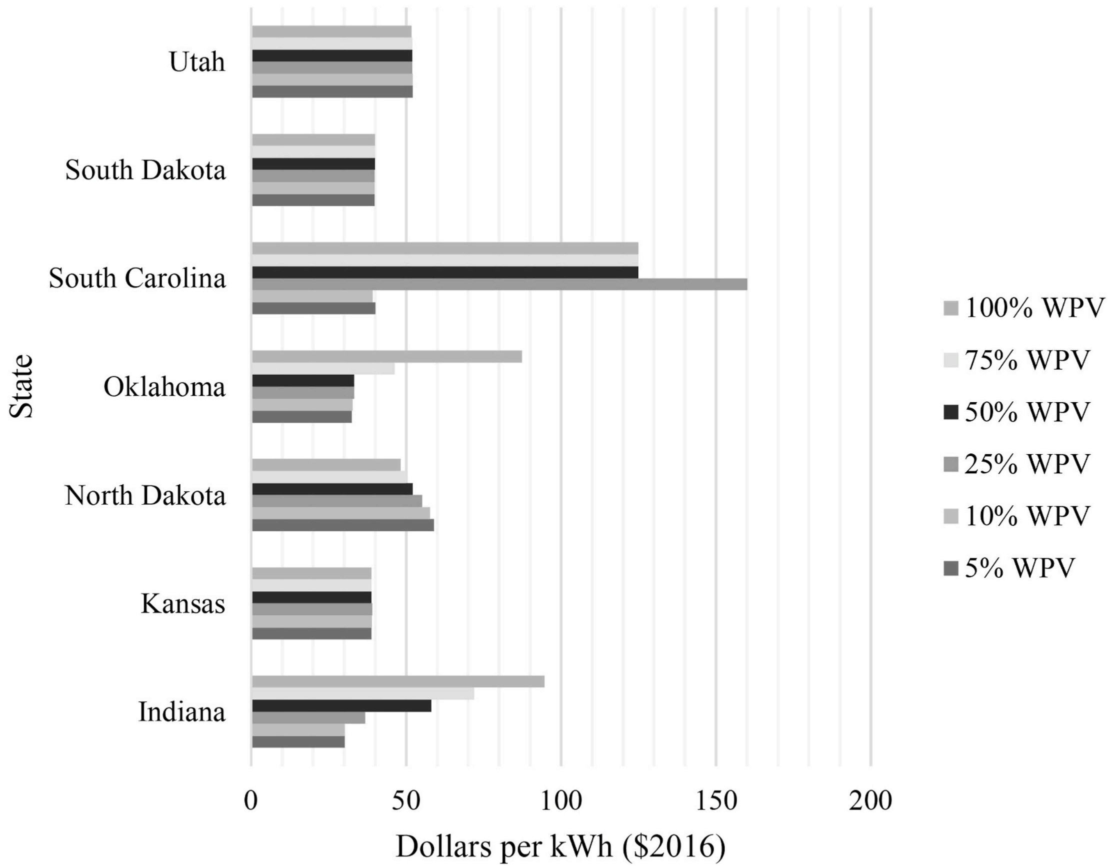

Fig. 5. Cost per unserved kWh electricity derived from the ICE Calculator ($2016) for states with active Renewable Portfolio Goal (RPG).

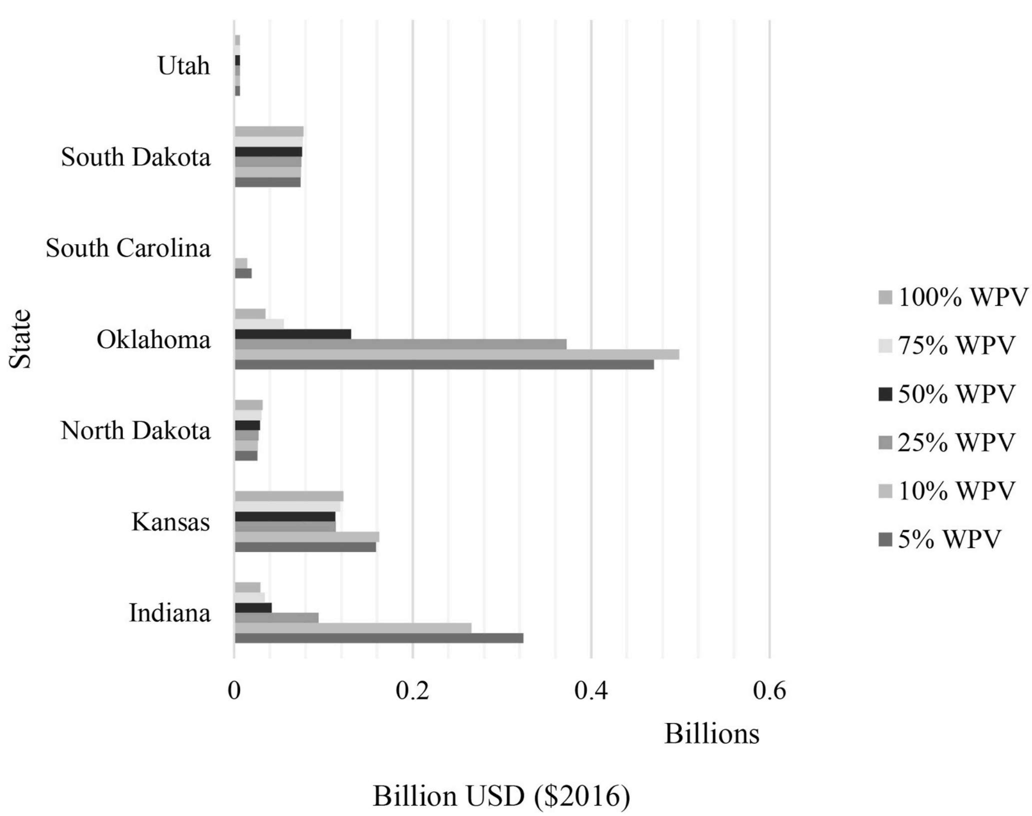

Fig. 6. Total costs of sustained power system interruptions ($2016) for states with active Renewable Portfolio Goal (RPG).

Table 8
Estimated average marginal effects for percentage increases in the net generation supplied by WPV.

State		Average Net Generation	Increases in GWh of Net Generation Supplied by WPV Corresponding to % Change				
			0%–5%	5%–10%	10%–25%	25%–50%	50%–75%
States with Renewable Portfolio Standards (RPS)							
Arizona	AZ	421,367	806	−4,747	−30,904	−134,812	−273,655
California	CA	311,844	1,403	−15,420	−96,732	−413,575	−834,167
Colorado	CO	147,433	663	−3,097	−20,572	−90,693	−184,703
Connecticut	CT	115	1	1	2	3	2
Delaware	DE	22	0	0	0	0	0
Hawaii	HI	25,748	116	1	−341	−2,288	−5,155
Iowa	IA	191,301	861	−5,470	−35,404	−153,973	−312,251
Illinois	IL	10,951	49	29	23	−272	−791
Massachusetts	MA	520	2	2	7	11	9
Maryland	MD	44	0	0	1	1	1
Maine	ME	1	0	0	0	0	0
Michigan	MI	297,472	1,339	−13,970	−87,836	−376,024	−758,740
Minnesota	MN	209,540	943	−6,653	−42,747	−185,183	−375,080
Missouri	MO	303,231	1,365	−14,543	−91,350	−390,857	−788,537
North Carolina	NC	568,095	2,556	−53,276	−327,327	−1,383,034	−2,778,850
New Hampshire	NH	7109	32	23	44	−59	−277
New Jersey	NJ	183	1	1	2	4	4
New Mexico	NM	41,474	187	−111	−1,226	−6,506	−13,946
Nevada	NV	112,235	505	−1,674	−11,560	−51,956	−106,436
New York	NY	80,478	75	27	−65	−839	−2,055
Ohio	OH	51,907	362	−758	−5,636	−26,201	−54,213
Oregon	OR	24	234	−233	−2,096	−10,485	−22,138
Pennsylvania	PA	207,491	0	0	0	1	1
Texas	TX	327,831	934	−6,514	−41,887	−181,533	−367,734
Virginia	VA	155,487	1475	−17,118	−107,131	−457,445	−922,266
Vermont	VT	220,398	15	13	33	27	−19
Washington	WA	421,367	700	−3,483	−22,996	−101,064	−205,627
Wisconsin	WI	311,844	992	−7,412	−47,446	−205,129	−415,217
States with Renewable Portfolio Goals (RPG)							
Indiana	IN	266,408	1199	−11,079	−70,074	−300,964	−607,923
Kansas	KS	89,679	404	−988	−7,137	−32,765	−67,548
North Dakota	ND	2773	12	11	29	29	−4
Oklahoma	OK	166,883	751	−4,067	−26,655	−116,696	−237,147
South Carolina	SC	183,227	825	−4,983	−32,374	−141,077	−286,277
South Dakota	SD	578	3	3	7	12	10
Utah	UT	650	3	3	8	13	11

5.1. OLS results

OLS estimation results in Table 4 imply utilities who identified wind or solar as a prime mover of at least one of their power plants can, on average, expect to experience shorter and less frequent power system disruptions, all else equal. Moreover, OLS results in indicate, all else equal, at low levels of net generation from WPV, one additional GWh of net generation from WPV will have a statistically significant positive impact on the frequency and duration of disruptions experienced by end-consumers (leading to increases in the values of *SAIFI* and *SAIDI* reported). However, if higher levels of net generation are already being supplied by WPV, then one additional GWh of net generation supplied by WPV has a statistically significant negative impact on the frequency and duration of disruptions experienced (leading to decreases in the values of *SAIFI* and *SAIDI* reported).

In other words, disruptions are decreasing as the net generation supplied by WPV is increasing. The effect of WPV on the duration of disruptions becomes negative when net generation exceeds 1,250 GWh (log-transformed value of *SAIDI* as the dependent variable) or exceeds 1,285 (IHS transformed value of *SAIDI* as the dependent variable). The effect of WPV on the frequency of disruptions experienced (as measured by IHS converted value of *SAIFI*) becomes negative when net generation from WPV exceeds 847 GWh.

5.2. IV results

The utilization of an IV specification produces parameter estimates that are strikingly similar to the parameter estimates provided by the OLS approach. IV results in Table 4 indicate all else equal, at low levels of net generation from WPV, one additional GWh of net generation from WPV will have a statistically significant positive impact on the duration of disruptions experienced by end-consumers (as measured by the log and IHS transformed value of *SAIDI*). At higher levels of net generation from WPV, one additional GWh of net generation from WPV is projected to have a statistically significant negative impact on the duration of disruptions experienced. The effect of WPV on the frequency of disruptions (as measured by the IHS transformed value of *SAIFI*) follows a similar pattern.

The effect of WPV on the duration of disruptions becomes negative when net generation exceeds 1,260 GWh (log-transformed value of *SAIDI* as the dependent variable) or when net generation exceeds 1,300 GWh (IHS transformed value of *SAIDI* as the dependent variable). Only six of the 276 utility companies in our sample (about 2% of the sample) generated more than 1,000 GWh of their annual net generation from WPV between 2013 and 2017. However, with current renewable support policies in place, relatively significant, non-marginal increases in the amount of net generation supplied by renewables (including WPV) are expected (or in some cases mandated).

To provide some perspective on the policy implications of our results, we projected disruptions in power system reliability, for all states with active renewable support policies in place. Projections are used to showcase how meeting future targets set by renewable support policies could impact power-system reliability in these states (Barbose 2017).[27] These projections were then used to predict the potential economic costs associated with disruptions in power system reliability. Costs were estimated using the Interruption Cost Estimator (ICE) calculator (Sullivan et al., 2018). Lastly, we evaluated the in-sample average marginal effect of increasing the percentage of current net generation being supplied by WPV for the same states.

5.3. Simulation results

The following section outlines the steps taken to project disruptions in power system reliability and estimate the associated economic costs. To begin, we identified states across the U.S. with active RPS or RPG in place (see Fig. 2).

Of these states, California, Hawaii, and Vermont were found to have the most aggressive renewable policy support programs in place.[28]

To forecast disruptions in power system reliability, data on the total annual net generation ($NetGeneration_{it}$) was used to estimate the amount of net generation associated with a given percentage increase in net generation from WPV for each utility. For example, if an individual utility reported net generation of 100,000 GWh, then a ten percent increase in WPV would yield 10,000 GWh. Based on the current policies in place across the U.S., our forecasting procedure considered increases in net generation from WPV, ranging from five to 100 percent.[29]

Results from the forecasting procedure are listed in Tables 5 and 6. Forecasted outcomes also considered other estimated model parameters.

Results suggest if WPV represented five percent of total net generation, then customers across states with active renewable support policies in place could expect, on average, to be without power for an additional 405 min (about 6 h and 45 min) per year. If net generation supplied by WPV exceeded 50%, all else equal, customers could expect to be without power on average for an additional 248 min a year. This implies that as WPV penetration grows over time, utilities are likely becoming better equipped to manage power system disruptions resulting from their use.

Utilities in Texas, a state with significant generation from wind installed already (~24.2 GW) and lower than average retail rates for electricity (~11.3 cents/kWh) (U.S. Energy Information Administration (EIA), 2019a; Electric Choice 2020), are not projected to experience any rapid increases in the duration or frequency of disruptions they experience from increasing net generation from WPV further. The same holds for Connecticut, Illinois, Massachusetts, Maryland, Maine, Pennsylvania, and Utah.

5.4. Estimating the costs of power system disruptions

To estimate the costs associated with the projected disruptions in power system reliability outlined above, we utilized the ICE Calculator, a publicly available tool co-developed by the Lawrence Berkeley National Laboratory and Nexcant Inc. (Sullivan et al., 2018). The ICE Calculator enables utilities, reliability planners, government organizations, and other interested parties to assess the economic benefits customers receive from improvements made to enhance the reliability of the power system (Sullivan et al., 2018).[30]

To produce economic cost estimates, the ICE calculator relies on data from 34 previously published papers that conduct customer interruption cost surveys (Sullivan et al., 2018).[31] It contains information from 105, 000 different customer surveys collected by ten different electric utilities between 1989 and 2012.[32] To utilize the ICE calculator, one needs to input information on the total number and type of customers (i.e., residential and non-residential) served by each utility, the state the utility operates in and the estimated values for disruptions in reliability of service (i.e., estimated values for *SAIDI* and *SAIFI*).[33]

The ICE Calculator produces estimates for four key outage cost metrics: (1) the cost per interruption event; (2) the cost per average kW; (3) the cost per unserved kWh of electricity (i.e., lost load); and, (4) the total cost of sustained interruptions. Based on the work of Sullivan et al. (2009), we estimated the economic costs of power system interruptions using metrics (3) and (4). Estimated values for *SAIDI* and *SAIFI* are those offered in Tables 5 and 6. To estimate the number of residential and non-residential customers, we multiplied the average total number of customers by the proportion of residential and non-residential customers served by utilities in the same state between 2013 and 2017, as reported on Survey Form EIA-861 (U.S. Energy Information Administration (EIA), 2019c).[34]

Table 7 outlines the results of this procedure for the states considered.

The results from our application of the ICE Calculator are listed below in Fig. 3 through 6.

Results suggest the average cost per unserved kWh of electricity is between \$51-\$62.[35] If WPV represent 25 percent of total net generation, then the cost per unserved kWh of electricity (for states with active renewable support policies) will range between \$30 to \$160. The cost per unserved kWh of electricity is projected to be highest in South

[27] Renewable support policies include both RPS and Renewable Portfolio Goals (RPG) which are similar to RPS except they do not mandate utilities to provide a certain percentage of their generation from renewables. Instead RPG are voluntary. Observations for Washington, D.C. which has an active RPS in place were excluded from our dataset to due data availability.

[28] California's RPS requires utilities to generate 33% of the electricity from renewable energy resources by the year 2020; 40% by the year 2024; 45% by the year 2027; and, 50% by the year 2030. Hawaii's RPS requires 100% of electricity supplied by utilities to end-consumers to be sourced from renewable resources by 2045. Vermont's RPS requires 55% of electricity generated to be supplied by renewables by 2017 and 75% by the year 2032.

[29] A detailed description of the forecasting procedure used for our analysis can be found in the Appendix.

[30] An economically efficient system reliability improvement is one in which the cost of improving the reliability of the system is less than or equal to the benefit customers receive from the utility making the improvement. Customer benefits are interpreted as the value of lost load or lost service and reported as the costs customers face during a disruption.

[31] The data provided was collected from individual utilities who in the interest of estimating the costs associated with customer interruptions, administered a set of surveys that described hypothetical interruptions and asked customers to estimate the costs they would incur if they experienced interruptions of varying duration, at different times of the day and during different seasons. Residential customers were asked to indicate the amount they would be willing to pay to avoid interruptions occurring under these conditions. Respondents were typically asked to estimate their costs for between four and eight hypothetical interruptions (Sullivan et al., 2009).

[32] For a complete outline of the methods used to estimate the interruption costs using customer survey data see Sullivan et al. (2015; 2018).

[33] While the ICE Calculator is a useful tool, it is important to note that it does have some limitations. For example, because the underlying costs estimates are based on hypothetical interruption scenarios presented in prior surveys, the ICE it is not designed to predict costs associated with power system interruptions that last longer than 32 h (1920 min). As a result, we are not able to predict outage costs for forecasted interruptions in power system reliability if the value of $SAIDI > 1920$. The same holds true if the value of $SAIFI \geq 100$ or if the value of the Custer Average Interruption Duration Index ($CAIDI) \geq 960$. It is important to note that the ICE Calculator assumes $CAIDI = \frac{SAIDI}{SAIFI}$ (Sullivan et al., 2018).

[34] For example, from 2013 to 2017, on average, 88% of the customers served by utilities in California were residential, while 12% were non-residential customers. The average number of customers served by utilities in the state of California from our data set is 935,728 customers. Therefore, when using the ICE calculator to predict outage costs, we assume there are 795,368 residential customers and 140,360 non-residential customers.

[35] The cost per unserved kWh of electricity represents the economic value customers place on reliability. It is sometimes referred to as the value of service (VOS) (Sullivan et al., 2018).

Carolina, a state with only a RPG in place. The average total cost of sustained power system interruptions is projected to be between $1.5 million to $2.5 trillion USD if net generation from WPV is between five and 100 percent of total net generation. The total cost of sustained power system interruptions includes the expenses that both customers and utilities face during prolonged periods of time without power (e.g., lost utility revenue).

5.5. Estimating average marginal effects

To estimate the marginal impact of increasing the net generation supplied by WPV, we consider the coefficient estimates for WPV_{it} and WPV_{it}^2 from the IV estimates of the IHS transformed values for *SAIDI* and the amount of annual net generation ($NetGeneration_{it}$) supplied by utilities within a given state. Net generation (by state) were aggregated, and next, the corresponding percentage increases in WPV were calculated to estimate the corresponding average marginal effects by state. The results are provided in Table 8.

Estimated marginal effects suggest, all else equal, increasing net generation supplied by WPV from 0 to 5%, increases the duration of disruptions experienced by end-consumers in all states. However, increasing net generation supplied by WPV has a negative impact on the duration of disruptions experienced for almost all states with active renewable support policies in place as net generation supplied by WPV surpasses 10% of total net generation. Marginal effects suggest that states whose average net generation is below the threshold of 1,285 GWh will experience longer power system interruptions from increasing net generation from WPV, all else equal than states whose average net generation supplied by WPV is above the threshold.

6. Conclusions and policy implications

In this study, we examined whether increases in net generation from WPV affect the frequency or duration of power system disruptions experienced by end-consumers. Our empirical analysis relied on data collected from two annual surveys: Survey Form EIA-861 and Survey Form EIA-923. We assumed end-user interruptions, as measured by two indices, *SAIDI* and *SAIFI,* could be used as proxies for in-service reliability, such that higher values of *SAIDI* and *SAIFI* indicate less reliability.

Using an unbalanced panel of 276 U.S. electric utility companies from 2013 to 2017, we modeled disruptions in reliability of service as a function of net generation supplied by WPV. We failed to reject our first null hypothesis that WPV does not affect the frequency with which power system disruptions occur (as measured by *SAIFI)*. Our results, however, do suggest that net generation from WPV does affect the duration of disruptions experienced by end-consumers (as measured by *SAIDI*). Thus, we rejected our second null hypothesis.

Specifically, results implied that initially, increased net generation from WPV had a statistically significant negative marginal effect on power system reliability. However, if net generation being supplied by WPV exceeds 1,200 GWh, the duration of disruptions is expected to decrease. Although our results imply that WPV may have a statistically significant negative marginal effect on power system reliability at low levels of net generation from WPV and a statistically significant positive impact on power system reliability at high levels of net generation, it is essential to note that these effects may not currently be economically significant. The marginal effect of WPV on power system reliability is small in magnitude and implies if net generation from WPV increases by one GWh, customers of utilities who source less than 1,200 GWh of their net generation from WPV can expect to experience power system outages lasting less than 1 min.

To provide some perspective on the economic and policy implications of our results, we forecasted disruptions in power system reliability, assuming different renewable energy penetration scenarios for states with active renewable support policies in place. Using these forecasts, we predicted the economic costs associated with increasing the percentage of net generation supplied by WPV using the ICE calculator. For more than half of the states, the forecasted results suggested if WPV generation exceeded 25 percent of total net generation, then disruptions in power system reliability will begin to decrease. The marginal effect of net generation from WPV, however, depends on whether or not the utility is currently sourcing a large amount (more than 1,000 GWh) of its net generation from WPV.

Over time, as the United States continues to transition to a renewable energy resource economy, there will be a continual need to assess both the benefits and costs of increases in net generation being supplied by WPV. As economically viable commercial storage technologies are relatively rare, energy storage technology options should also continue to be explored for achieving emissions reductions targets using WPV. Furthermore, without a sustainable supply of battery storage capacity, back-up generation (e.g., natural gas) will continue to be necessary for supporting the U.S. electrical grid and meeting power demand.

One potential limitation of this study is that the current structure of the U.S. electric grid is primarily based on centralized generation and the unidirectional flow of electrons through the system. All of our estimates of disruptions and total costs are based on the electric grid in its current form. As the system continues to evolve to distributed generation and the use of microgrids, the power flows will likely become bidirectional within the system. Given this evolution, the grid will arguably become more reliable and resilient to future disruptions (Kiesling et al., 2019). If this evolution continues as expected, then our estimates may overstate these estimated disruptions.

Another potential limitation of this study is our data on WPV are based entirely on "front-of-the-meter" units (i.e., utility-scale renewables), and does not include "behind-the-meter" units (such as privately-owned rooftop solar panels) since their operations are often not observed by the utility. Since our data does not account for all of the behind-the-meter renewables, then our disruption estimates may understate the duration and costs in the near future. These limitations suggest future areas of related research on power system disruptions stemming from different energy sources focusing on the potential mitigating effects of microgrids, and the potential additional costs of disruptions from "behind-the-meter" renewable energy units.

Energy policy and management in the United States, whether energy is generated from non-renewable or renewable resources, is a combination of public and private decisions at the national, regional, state, and local levels. For example, power-generation corporations follow a private business model, but are subject to government oversight and regulation, particularly for pricing. Although seeking to maximize profits, power-generation corporations also respond to customer concerns regarding social issues such as environmental protection and sustainability.

Currently, there is much concern in the United States and throughout the world about the adverse environmental effects of greenhouse gas emissions from the burning of fossil fuels, including for power generation. Greenhouse gas emissions are considered a negative externality, so there is justification from an economic theory perspective for the implementation of public policies to "fix" the externality problem.

Following an incentive-based policy approach, federal and state governments can and do provide economic subsidies to utilities to encourage increased power generation from wind, solar, and other renewables (e.g., tax subsidies). Following a direct-regulation policy approach, state and local governments are imposing standards on utilities, which require that the utility generate power using a mandated percentage of wind, solar, and other renewables (e.g., RPS). These policies benefit power customers and society by reducing the harmful environmental effects of greenhouse gas emissions. However, as shown in this study, these policies also impose costs to power customers and society caused by power interruptions.

The full costs of increasing generation from renewable power sources along the grid, which our results show vary across states and regions, need to be accounted for when assessing the benefits and costs of state and local public policies aimed at increasing power generation from WPV. Failure to account for these costs can lead to inefficient policy and management decisions on the part of private utilities, government agencies, and elected officials. Recognition and quantification of these costs may also help utilities to discover new means for improving the grid's ability to absorb additional generation from renewables, thereby reducing interruption costs. Reducing interruptions costs is a win-win-win for the "triple bottom line" as it will help the profitability of utilities, help to improve the environment, and improve overall social well-being. That is, recognition of these unintended costs can make public policies for promoting renewable energy more attractive from an economic perspective.

Author's contributions

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. Each author contributed to the conception and design of the work. We further confirm authors have approved the order of authors listed in the manuscript. The authors would like to ackowledge the assistance of F. Bert Steele in proofreading the manuscript. We understand that the Corresponding Author (Amanda J. Harker Steele) is the sole contact for the editorial process (including Editorial Manager and direct communications with the office). She is responsible for communicating with the other authors about progress, submissions of revisions, and final approval of proofs. We confirm that we have provided a current, correct email address which is accessible by the Corresponding Author.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2020.111947.

Notes: (i) Data were provided from Survey Form EIA-861, Survey Form EIA-923, IRS Form 8835, and Berkley National Lab's RPS Percentage Targets by State between 2013 and 2017.

References

Barbose, G., 2017. U.S. Renewable Portfolio Standards: 2017 Annual Status Report. Lawrence Berkley National Lab. Retrieved from. https://eta-publications.lbl.gov/sites/default/files/2017-annual-rps-summary-report.pdf.

Bergstrom, J.C., Randall, A., 2016. In: Resource Economics: an Economic Approach to Natural Resource and Environmental Policy, fourth ed. Edward Elgar Publishing.

Bird, L., Milligan, M., Lew, D., 2013. Integrating Variable Renewable Energy: Challenges and Solutions. Golden, CO. National Renewable Energy Laboratory. Retired from. https://www.nrel.gov/docs/fy13osti/60451.pdf.

Burtraw, D., Palmer, K., Paul, A., Beasley, B., Woerman, M., 2013. Reliability in the U.S. Electricity industry under new environmental regulations. Energy Pol. 62, 1078–1091.

California ISO, 2016. What the Duck Curve Tells Us about Managing a Green Grid. Retrieved from. https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf.

Cameron, A.C., Trivedi, P.K., 2009. Microeconometrics Using Stata. Stata press.

Cleary, K., Palmer, K., October 28, 2019. Planning for resilience in a renewable-dominated world. Resources. Resources for the Future. Retrieved from. https://www.resourcesmag.org/common-resources/planning-resilience-renewable-dominated-world/.

Department of Energy (DOE), 2015. Energy storage. Retrieved from. https://www.energy.gov/.

Electric Choice, 2020. Electricity Rates by State. Retrieved from. https://www.electricchoice.com/electricity-prices-by-state/.

Eto, J.H., LaCommare, K.H., 2008. Tracking the Reliability of the U.S. Electric Power System: an Assessment of Publicly Available Information Reported to State Public Utility Commissions. " Ernest Orlando Lawrence Berkeley National Laboratory.

Eto, J.H., LaCommare, K.H., Larsen, P., Todd, A., Fisher, E., 2012. Distribution-level electricity reliability: temporal trends using statistical analysis. Energy Pol. 49, 243–252.

Federal Energy Regulatory Commission (FERC), 2018. Distributed energy resources. Technical considerations for the bulk power system. " Retrieved from. https://www.ferc.gov/CalendarFiles/20180215112833-der-report.pdf.

Fenrick, S.A., Getachew, L., 2012. Formulating appropriate electric reliability targets and performance evaluations. Electr. J. 25 (2), 44–53.

Hausman, J.A., 1978. Specification tests in econometrics. Econometrica 46, 1251–1271.

Henry, D., Ramirez-Marquez, J.E., 2016. "On the impacts of power outages during Hurricane Sandy – a resilience-based analysis. Syst. Eng. 19 (1), 59–75.

Hines, P., Apt, J., Talukdar, S., 2009. Large blackouts in North America: historical trends and policy implications. Energy Pol. 37, 5249–5259.

Imelda, M. Fripp, Roberts, M.J., 2018. Variable Pricing and the Cost of Renewable Energy. NBER Working Paper Series, Working Paper 24712. Retrieved from. https://www.nber.org/papers/w24712.pdf.

Institute of Electrical and Electronics Engineers (IEEE), 1998. Trial Use Guide for Electric Power Distribution Reliability Indices, P1366/D19. Retrieved from. http://www.pti-us.com/pti/ieee/p1366d~3.htm.

Johnson, N., 1949. Systems of frequency curves generated by methods of translation. Biometrika 36, 149–176.

Johnson, E.P., Oliver, M.E., 2019. Renewable generation capacity and wholesale electricity price variance. Energy J. 40 (5), 143–168.

Kiesling, L., Munger, M., Theisen, A., 2019. From Airbnb to Solar: toward a Transaction Cost Model of a Retail Electricity Distribution Platform. Social Science Research Network. Retrieved from. https://ssrn.com/abstract=3229960.

Larsen, P., Hamachi-LaCommare, K., Eto, J., Sweeney, J., 2015. Assessing Changes in the Reliability of the U.S. Electric Power System. Lawrence Berkeley National Laboratory, " Berkeley.

Larsen, P., LaCommare, K., Eto, J., Sweeney, J., 2016. Recent trends in power system reliability and implications for evaluating future investments in resiliency. Energy 117, 29–46.

Malla, K., 2013. The Effects of Quality Standards on Electricity Service Reliability [Thesis]. " Illinois State University. Retrieved from. https://irps.illinoisstate.edu.

National Conference of State Legislatures (NCSL), 2019. State renewable portfolio standards and goals. " Retrieved from. https://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx.

North American Electric Reliability Corporation (NERC), 2018. August. Bulk Electric System Definition Reference Documentation. Retrieved from. https://www.nerc.com/pa/Stand/2018%20Bulk%20Electric%20System%20Definition%20Reference/BES_Reference_Doc_08_08_2018_Clean_for_Posting.pdf.

Nikoletatos, J., Tselepis, S., 2015. Renewable Energy Integration in Power Grids: Technology Brief. " IEA-ETSAP and IRENA Technology Brief.

Newburger, E., October 26, 2019. "More than 2 million people expected to lose power in PG&E blackout as California wildfires rage," *CNBC*. Retrieved from. https://www.cnbc.com/2019/10/26/pge-will-shut-off-power-to-940000-customers-in-northern-california-to-reduce-wildfire-risk.html.

Prol, J.L., Steininger, K.W., Zilberman, D., 2020. The cannibalization effect of wind and solar in the California wholesale electricity market. Energy Econ. 85, 1–15.

Sherlock, M., 2020. The renewable electricity production tax credit. Retrieved from. https://fas.org/sgp/crs/misc/R43453.pdf.

Skea, J., Anderson, D., Green, T., Gross, R., Heptonstall, P., Leach, M., 2008. Intermittent renewable generation and the cost of maintaining power system reliability. IET Gener., Transm. Distrib. 2 (1), 82–89.

Sullivan, M., Mercurio, M., Schellenberg, J., 2009. Estimated Values of Service Reliability for Electric Utility Customers in the United States. Lawrence Berkeley National Lab, " Berkeley.

Sullivan, M., Schellenberg, J., Blundell, M., 2015. Updated Value of Service Reliability Estimates for Electric Utility Customers in the United States. Lawrence Berkeley National Lab, " Berkeley.

Sullivan, M., Collins, M.T., Schellenberg, J., Larsen, P.H., 2018. Estimating Power System Interruption Costs: A Guidebook for Electric Utilities. Lawrence Berkeley National Lab. Retrieved from.
U.S. Energy Information Administration (EIA), 2017. "What is U.S. Electricity generation by source?". Retrieved from. https://www.eia.gov.
U.S. Energy Information Administration (EIA), 2019a. Texas ranks first in U.S.- installed wind capacity and number of turbines. Retrieved from. https://www.eia.gov/todayinenergy/detail.php?id=40252.
U.S. Energy Information Administration (EIA), 2019b. Investor-owned utilities served 72% of U.S. Electricity in 2017. Retrieved from. https://www.eia.gov/todayinenergy/detail.php?id=40913#.
U.S. Energy Information Administration (EIA), 2019c. Detailed State Data. Retrieved from. https://www.eia.gov/electricity/data/state/.
U.S. Energy Information Administration (EIA), 2020. New electric generating capacity will come primarily from wind and solar. Retrieved from. https://www.eia.gov/todayinenergy/detail.php?id=42495.
Wangdee, W., 2014. Reliability Impact of intermittent renewable energy source integration into the power system. In: Electrical Engineering Congress (iEECON), 2014 International. IEEE, pp. 1–4.
Wiser, R., Porter, K., Grace, R., 2005. Evaluating experience with renewable portfolio standards in the United States. Mitig. Adapt. Strategies Glob. Change 10 (2), 237–263.
Wooldridge, J.M., 2010. Econometric Analysis of Cross Sectional and Panel Data. MIT Press, Cambridge, MA.