Role of Variable Renewable Energy Penetration on Electricity Price and its Volatility Across Independent System Operators in the United States

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Abstract

The U.S. electrical grid has undergone substantial transformation with increased penetration of wind and solar - forms of variable renewable energy (VRE). Despite the benefits of VRE for decarbonization, it has garnered some controversy for inducing unwanted effects in regional electricity markets. In this study, we examine the role of VRE penetration on the system electricity

price and price volatility based on hourly, real-time, historical data from six Independent System Operators in the U.S. using quantile and skew t-distribution regressions. After correcting for temporal effects, we observe a decrease in price, with non-linear effects on price volatility, for an increase in VRE penetration. These results are consistent with the modern portfolio theory where diverse volatile assets may lead to more stable and less risky portfolios.

Introduction

The U.S. electrical grid is undergoing a transformation with respect to the diversity of assets in its energy portfolio with substantial integration of renewable energy technologies, particularly variable renewable energy (VRE) technologies —non-dispatchable technologies with changing output dependent on renewable resource availability, such as solar and wind power. Although the majority of energy generation comes from fossil fuels, total energy generated from renewable resources (hydroelectric power included) accounted for 18% of total generation in the United States in 2020 with variable sources - wind and solar energy - accounting for 10.7% of the total generation (*1*). This is owing to increased build-out of renewable energy projects facilitated by the ebbing cost of installation and favorable policy initiatives (*2*). By 2021, an estimated 27.6 GW of renewables is planned to come online with 12.2 GW from wind and 15.4 GW from utility-scale solar (*3*). While the addition of renewable energy will help accelerate the decarbonization of the power sector, its optimal integration will require substantial changes in power system design and market regulations to accommodate the inherent variability of these resources on the electric grid (*3*). To do this, it is important to elucidate an understanding of the role of VRE on electricity price and price volatility (both with respect to time and VRE penetration), as these impact the entire electricity value chain from the energy producers to the consumers.

Several papers have explored the relationship between electricity price and VRE penetration of wind (*4–12*), solar (*13, 14*), or both (*15–19*). Some of these papers have used simulated data (*11, 13, 17*), while others have used historical data (*4, 5, 7–10, 12, 14, 15, 18, 19*). A few have combined simulated data with historical data validation (*6, 16, 20, 21*). The methods used in these studies have primarily been multivariate linear regressions (*4, 5, 7, 9–12, 14–16, 18, 19, 22, 23*) or visualizations with descriptive statistics (*24, 25*). It is worth noting that the optimization methods in production cost models for most of the scenario-type/simulation-based analyses (*6, 13, 17, 26*) are often based on linear assumptions. These methods are, however, limited in that they assume a linear relationship between eletricity price and VRE with constant variance, but there are inherent distributional changes in the electricity price with respect to VRE requiring more robust modeling choices. One alternative approach has been applied to a case study of PJM using the Robust Linear Weighted Regression (*8*); however, the scope is limited to a single ISO and one year of data. In general, increasing penetration of VRE is associated with a lower average wholesale price of electricity. This behaviour has been found in both domestic (*4–6, 8–12, 12–19, 26*) and some international (*22–25, 27, 28*) electricity markets. A summary of the domestic studies can be found in *Supplementary Materials (Table S1)*. Using the robust methods in this study, our results not only corroborate the existing literature on increased VRE penetration leading to a reduction in electricity price, but also illustrate that this effect is nonlinear and the greatest impact can be seen in the reductions in extremely high system electricity prices with increased VRE.

Negative system electricity price is also a characteristic of the modern electricity market. Negative prices occur as a result of generation-demand imbalance resulting in high supply during times of low demand. Several factors contribute including a substantial decrease in demand, limited flexibility in power plant operations (e.g., slow or expensive ramping, limited energy storage), and limited transmission capacities. Studies of some electricity markets have attributed higher frequency of negative prices to high penetrations of VRE (*25, 29*). One study found that extreme negative prices - the result of electricity oversupply - are highly correlated with periods of high wind penetration (*25*). However, our study did not find a relationship between the frequency of negative electricity prices and VRE, with inconsistent behaviour observed across the ISOs studied.

While the literature on the average behaviour of electricity price and VRE penetration has been consistent, its price volatility effects with respect to time (temporal price volatility) has been a topic of controversy. Some studies find evidence of an increase in temporal price volatility as VRE penetration increases (*4, 22, 26, 30*), while others are unable to show significant evidence that increasing the share of VRE leads to high temporal price volatility (*31, 32*). A case study of Germany and Denmark found that increasing penetration of VRE could either increase or decrease the temporal price volatility (*33*). While studies have often found that high wind energy penetration contributes to high temporal price volatility (*4, 6, 22*), a study in South Korea showed that temporal price volatility decreases as wind penetration increases up to 10% since the wind profile matches the demand patterns at this penetration (*34*). There are also instances where solar energy penetration have abated temporal price volatility (*33, 35*). The evidence from literature suggests that the relationship between temporal price volatility and VRE penetration can vary widely as a result of a confluence of several factors, including patterns of demand (*34*), weather (*22*), and the availability of flexible generation (*33*). In 5 of the 6 ISOs we studied, the system temporal price volatility decreased as the penetration of VRE increased across all quantiles. Our results are consistent with the modern portfolio theory that posits that the portfolio of diverse and uncorrelated (or low correlated) assets leads to price volatility reduction (*36*). Similar to the finance field, we show that adding diverse and volatile assets can lead to a less risky portfolio of such energy assets.

In this study, we use robust methods, quantile regression and skew-t distribution regression, to evaluate the impact of VRE penetration on electricity price and price volatility. We define volatility both with respect to time (temporal price volatility) and VRE penetration. Quantile regression and skew-t distribution regression have been chosen since they are well suited for handling outliers, non-linearity, and skewness.

This analysis examines 6 of the 7 Independent System Operator (ISO) regions in the United States shown in Fig. 1 (excluding Electricity Reliability Council of Texas, ERCOT) and corresponding data is described in *Supplementary Materials* (Table S2). At this time, the ERCOT region has been excluded from this analysis due to data constraints that make a comparable analysis infeasible. Despite this, to the best of our knowledge this is the most comprehensive study of the role of VRE on system electricity price and price volatility at the national scale for the United States using robust, nonlinear methods.

The chosen methodology for exploring the relationship between VRE and system electricity price and price volatility in several ISOs in the United States has applicability in the broader international context. We note that some international studies have explored this relationship in Italy (*24*), Germany (*22, 24*), South Australia (*25*), Spain (*24, 28*), Denmark (*22, 27*), and South Korea (*34*). Our approach captures non-linearity and distributional effects and can be applied to other electricity markets. Our findings also have a broader context in relation to modern portfolio theory with respect to the addition of a highly volatile asset, VRE, and a corresponding reduction in electricity price and volatility. However, it is important to note that though our methodological approach can be extended to other electricity markets to explore the relationship between VRE and system electricity price or price volatility, the actual trend and relationship may inherently differ in each context owing to several factors, such as the amount of VRE penetration, and the policies and regulations that govern the local electricity market.

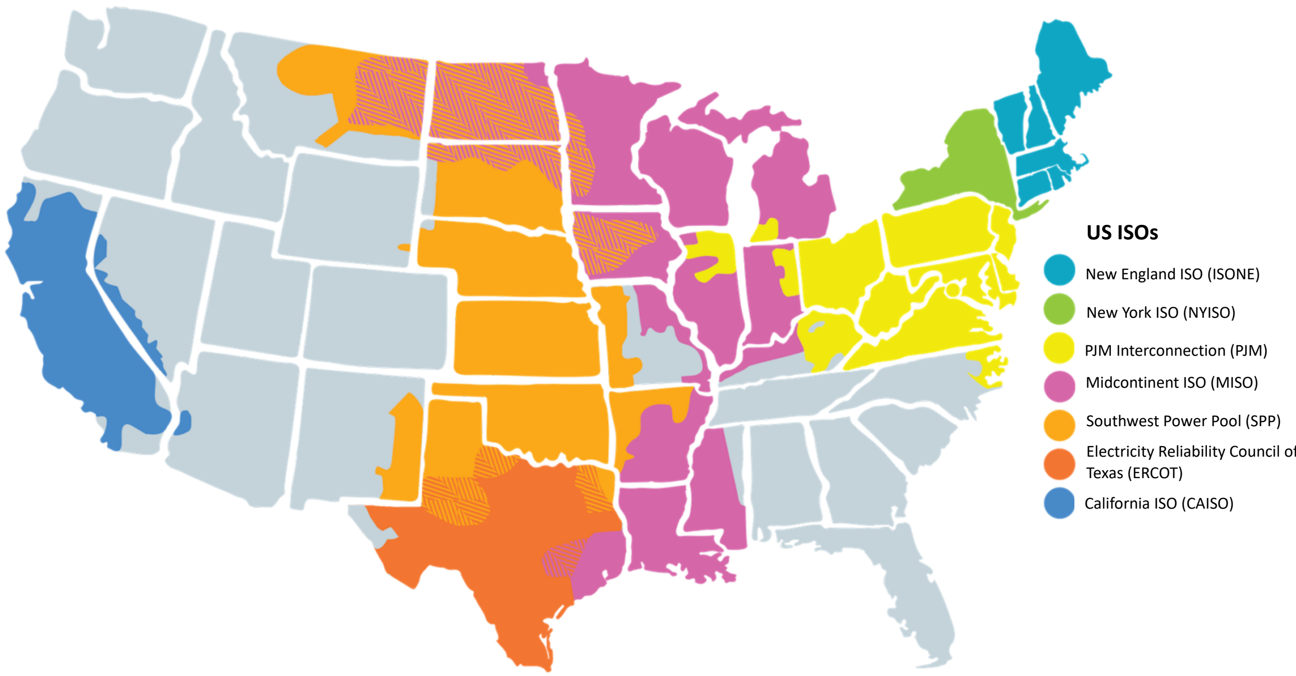

Fig. 1. Map of Independent System Operators (ISOs) in the United States. ISOs are responsible for coordinating, controlling and monitoring electricity grid within their region of control. As shown here are 7 ISOs in the United States and the regions covered by these ISOs accounting for 67% of the total electricity demand in the country. Adapted from (*37*)

VRE Penetration and System Electricity Price

Renewable energy resources and the adoption of utility-scale VRE technologies varies substantially throughout the United States, as seen in the corresponding VRE generation shares across ISOs in *Supplementary Materials* (Fig. S3). In order to accurately assess the role of VRE on system electricity price, a comparative analysis across multiple ISOs was performed using regional data from 2014-2020 when available. Details on the regional data used for each ISO can be found in *Supplementary Materials* (Table S2). The system electricity price is based on the real-time wholesale price of electricity excluding the congestion costs and transmission losses (see *Supplementary Materials* (Materials and Methods: ISO Specific Procedures) for details).

Corrections were also made for the diurnal, seasonal, and weekend effects that may influence demand and resource availability and ultimately impact price as described in *Supplementary Materials* (Materials and Methods: Seasonal and Diurnal Adjustment) and shown in Fig. S1. Descriptive statistics for the electricity price and temporal price volatility after applying these corrections, can be seen in Table 1. For each ISO studied, the mean system electricity price is substantially larger than the median price, indicating skewness and price outliers, suggesting that the ordinary least squares approach applied in the majority of the previous studies using multivariate linear regression (*4, 5, 7, 9–12, 14–16, 18, 19, 22, 23*) may not have adequately captured the dynamics of the existing relationship between VRE penetration and electricity price.

	CAISO	ISONE	MISO	NYISO	PJM	SPP
Price($)						
min	-31.57	-156.86	-15.76	-2498.82	-56.71	-33.65
median	27.12	25.85	23.84	19.15	25.59	17.23
max	1000.00	2446.71	578.53	1175.95	654.64	1127.16
mean	33.82	34.44	27.23	21.01	30.83	20.35
sd	43.72	36.10	16.04	36.83	21.75	28.58
Price Volatility($)						
min	0.00	0.00	0.01	0.01	0.01	0.01
median	2.57	2.58	1.24	2.12	1.70	2.12
max	625.44	1140.54	350.49	1377.07	374.30	759.84
mean	9.80	5.48	3.64	5.85	4.64	7.27
sd	32.66	15.17	9.99	25.04	9.93	22.59
Percentage of VRE(%)						
min	0.04	-0.02	0.04	0.00	0.01	1.64
median	7.06	2.74	7.56	2.44	2.22	29.39
max	38.51	17.64	27.78	15.24	9.16	66.95
mean	9.77	3.37	8.47	3.26	2.63	30.24
sd	8.05	2.58	5.24	2.82	1.79	15.14

Table 1. Descriptive Statistics Summary. This shows the minimum, median, maximum and mean statistics for the system price (in \$) and temporal price volatility (in \$). (Note: sd = standard deviation)

The quantile regression results in Fig. 2 show that an increase in the penetration of VRE results in a decrease in system electricity price. While this trend is generally true across all ISOs and quantiles (25%, 50%, and 75%), the relative system price reduction is often greatest in the extreme prices, i.e., the 90% quantile. Additionally, the change in the system price is not constant across the percentage of VRE nor the quantiles and, once again, this is typically more apparent at higher quantiles. For example, in PJM, Fig. 2 C, when the VRE percentage changes from 0-1% the median detrended system price decreases by \$0.37 USD in average absolute values and the 90th percentile of the detrended system price decrease by \$6.96 in average absolute values but when the VRE percentage changes from 5-6% the median detrended system price decreases by \$0.51 in average absolute values and the 90th percentile detrended price decreases by \$2.56 in average absolute values. The derivative of the detrended system price with respect to the percentage of VRE is depicted in *Supplementary Materials (Fig. S4)*. It is evident that increasing penetration of VRE lowers the frequency of occurrence of higher extremes of system prices.

The results from the skew-t distribution regression in Fig. 3 also show the distributional effects of increasing VRE on price. We estimated a decreasing trend in skewness with VRE for all ISOs. The skewness approaches symmetry with increasing VRE for four of the ISOs suggesting that as VRE is increased there is a lower frequency of large price extremes above the average price. The magnitude and duration of these price spikes are particularly harmful to electricity retailers who cannot pass on price risk to customers (*38*). The main contribution to the pattern towards symmetry is the decrease in large, positive fluctuations from the average price. We see that skewness decreases to negative for SPP and CAISO which implies that as VRE increases in these systems it is more likely to have deviations of detrended price below average. It is worth noting that these two regions (SPP and CAISO) also have the highest levels of VRE penetration.

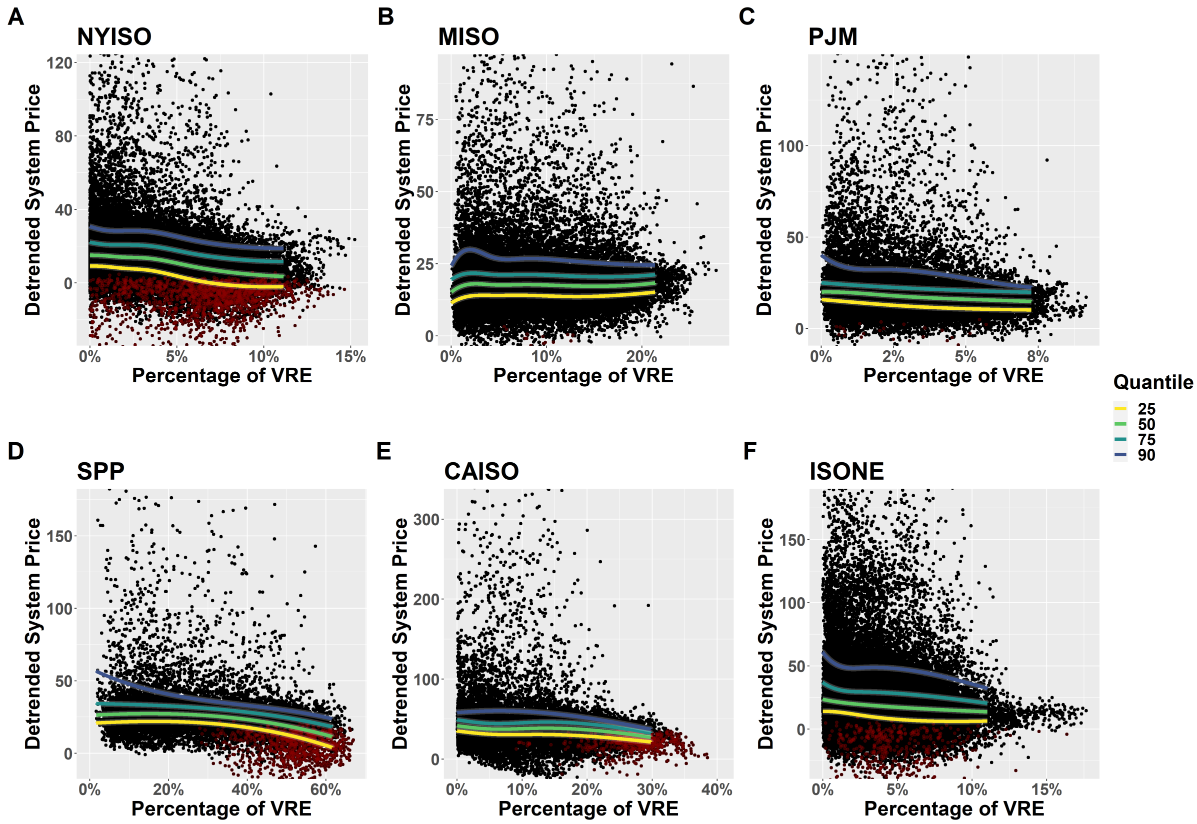

Fig. 2. VRE penetration (in %) and Electricity Price (in \$). A, B, C, D, E and F show the relationship between VRE penetration and Electricity price for NYISO, MISO, PJM, CAISO, ISONE and SPP respectively. The continuous lines show the quantiles with the colors - yellow, green, blue and purple representing the 25th, 50th (median), 75th and the 90th percentiles respectively.

Our results for the system price reduction is consistent with the merit order effect of renewables where conventional generation assets are unprofitable in the market when there is a high penetration of VRE. This occurs because VREs tend to have lower marginal operating costs and are, therefore, prioritized in satisfying demand. This effect has been well studied and observed in electricity markets in several countries (*25, 34, 39–48*). The lowering of electricity prices as VRE penetration increases is advantageous for consumers but not necessarily for the generators/suppliers since this causes a reduction in the income from electricity sold in the market.

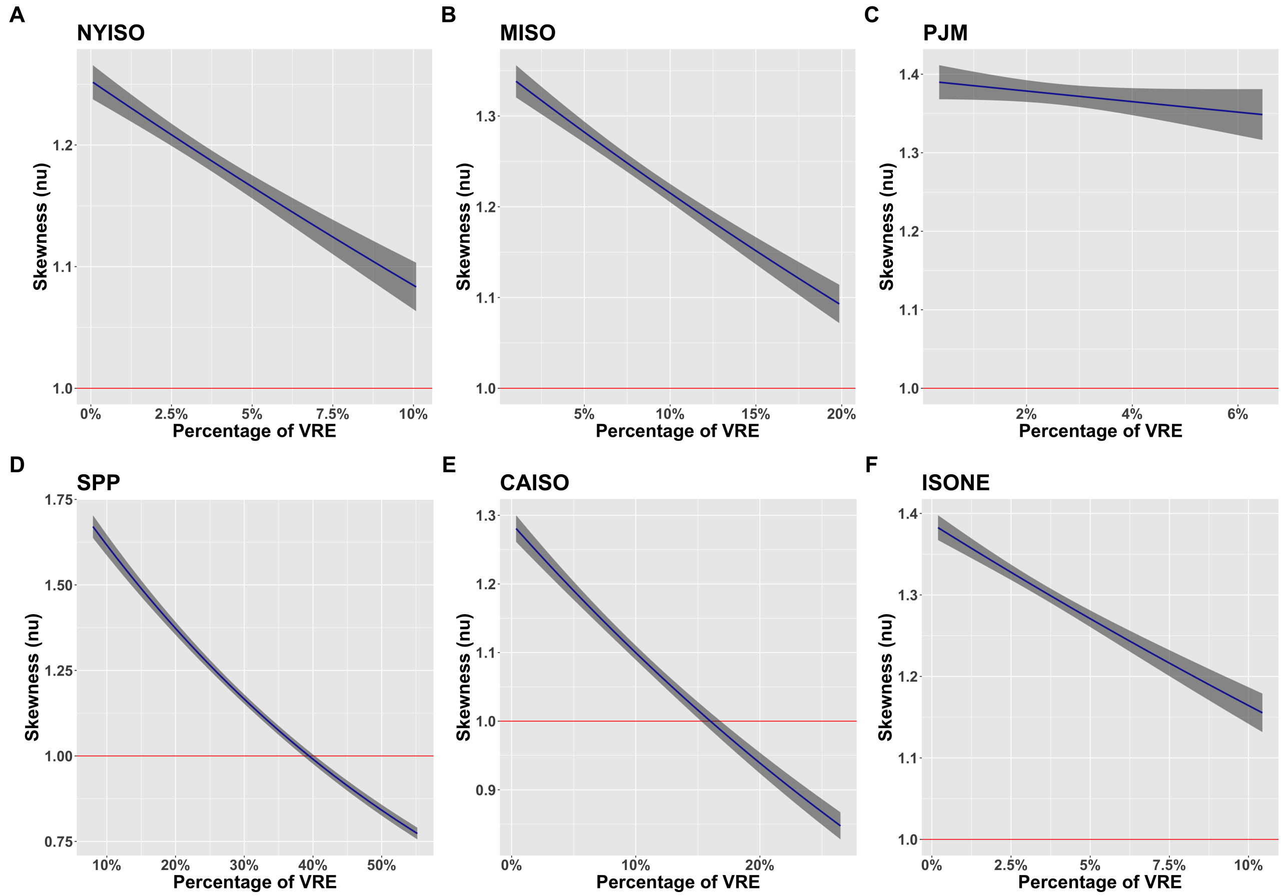

Fig. 3. Estimated effects of VRE percentage on the skewness (nu) parameter for a skewed t-distribution for detrended price using a log link. Gray bands indicate the 95% confidence intervals. The reference line at 1 denotes symmetry.

However, the lower cost electricity can attract energy-intensive industries, increasing electricity demand within the ISO, allowing generators/suppliers to increase revenues from increased production. Additionally, not all generators are affected equally and some, particularly those with flexible generation assets, may benefit from increased VRE penetration since they can contribute flexible reserves to manage VRE variability (*49, 50*). Apart from attaining a sustainable price level (*48*) which is good for end users, the merit order effect can also help to promote flexibility in the market to incorporate flexible generation assets that can ramp up and down in response to increasing VRE penetration. It can also incentivize storage and demand response technologies. Security of supply is another concern since the merit order effect may lead to the shut down of conventional plants; however, this risk can be reduced with the introduction of capacity markets (*48*). Lowering the system electricity price may increase the cost of some sustainable energy policies, such as feed-in-tariffs (*45*), and may lead to lower cost flexible natural gas plants replacing nuclear plants and, consequently, producing more emissions (*51*). Careful policy design will be needed to mitigate these effects.

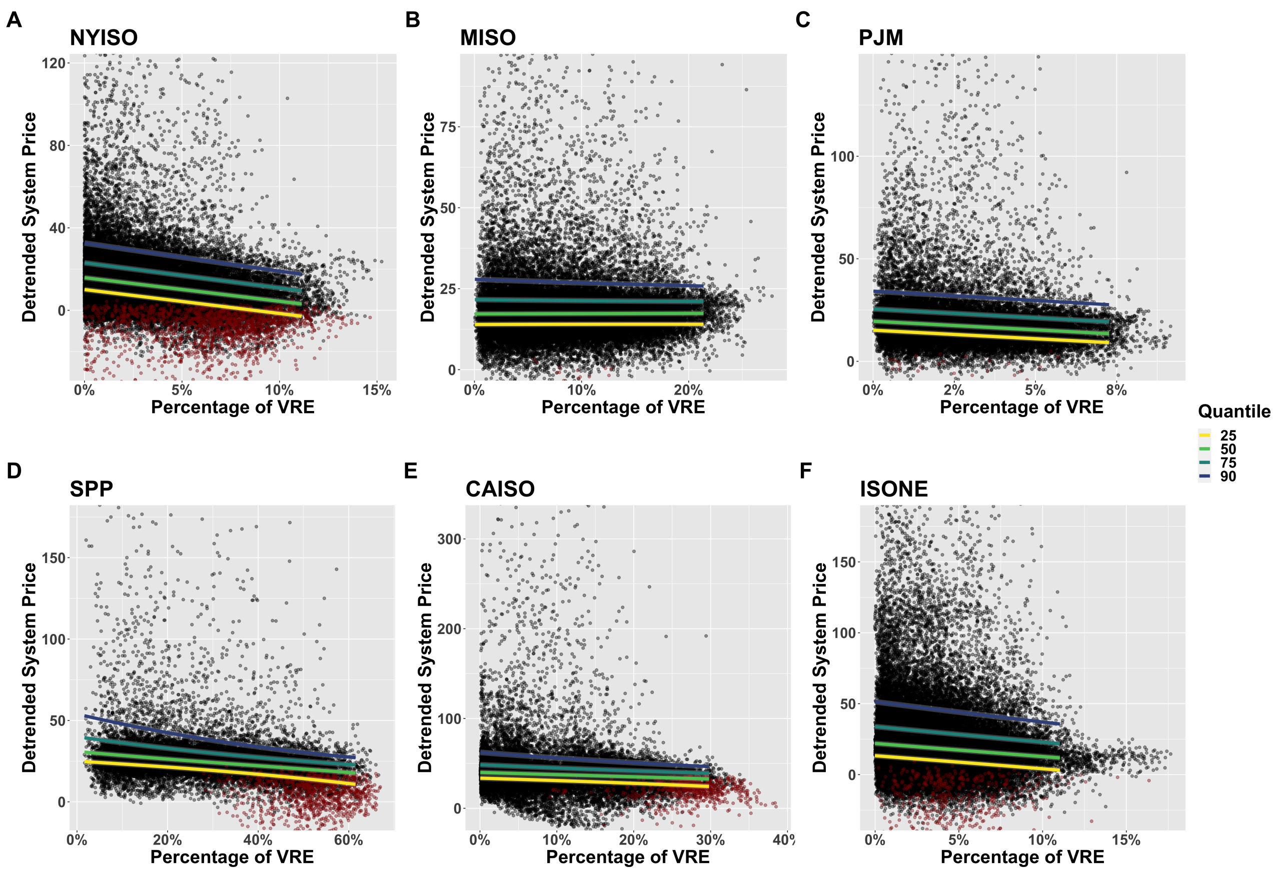

Fig. 4. Quantiles of skew t-distribution based on the estimated pointwise means of the parameters listed in Table S4. Points correspond to seasonally detrended system price and y axis is trimmed to inner 99% of detrended price; red points correspond to a negative price before seasonal detrending.

Negative prices are the extreme end-products of oversupply of electricity. It is most common in markets with large amount of nuclear, hydroelectric, and wind generation (*52*). However, conventional resources also play a role in driving down prices (at least in the short term) as generators from these inflexible assets often prefer not to shut down or reduce their output when there is high amounts of VRE because of technical and economic costs related to output reduction and regulation costs (in the case of hydroelectric power - for compliance with environmental regulations for water flow to maintain fish population) (*52*). The trend of negative system price (based on the original raw data without correction for temporal effects) with increasing VRE penetration varies for different ISOs (shown in the red colored points in Fig. 2 and Fig. 4). However, the frequency of negative detrended system price decreases with VRE penetration for all ISOs studied except SPP - which shows an increase in the frequency of negative detrended system price as VRE penetration increases. This observation might suggest that among other factors increased VRE penetration is not solely responsible for increased frequency of negative system electricity prices but rather due to a combination of other factors such as seasonal, daily and weekend temporal effects.

VRE Penetration and System Electricity Price Volatility

The system electricity price varies as a function of both time and VRE penetration. Firstly, to calculate the volatility of system electricity price as a function of time (temporal price volatility), we use the Exponential Weighted Moving Average (EWMA) volatilitty - an approach that uses a penalized model with weights that decrease in time - (see *Supplementary Materials (Materials and Methods: Nonparametric quantile regression)*) and compare the temporal price volatility with the VRE penetration. The temporal price volatility measure used in this study has roots in historical volatility popularly used in finance. This method of calculating volatility is based on the operation stage volatility (realised effects) and should not be confused with planning stage volatility that attempts to capture differences between the predicted and observed real-time price variations (predicted effects) (*30*). Secondly, to assess the variability of system electricity price as a function of VRE penetration, we evaluate the distributional characteristics of the skew-t model.

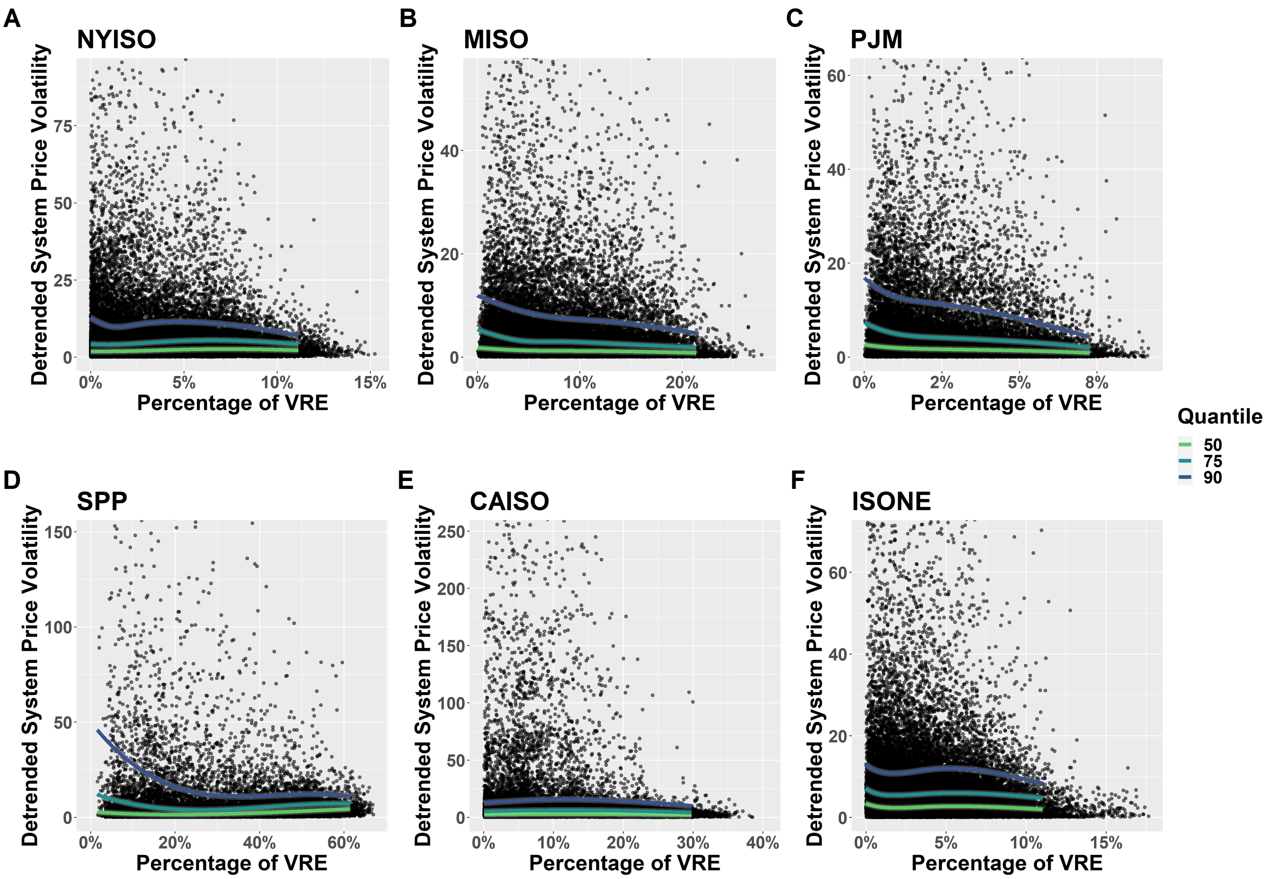

Fig. 5. VRE penetration (in %) and temporal price volatility (in \$). A, B, C, D, E and F show the relationship between VRE penetration and temporal price volatility for NYISO, MISO, PJM, CAISO, ISONE and SPP respectively. The continuous lines show the quantiles with the colors - yellow, green and purple representing the 50th (median), 75th and the 90th percentiles respectively.

The results for the quantile regression on EWMA price volatility (temporal volatility), shown in Fig. 5, indicate that there is a reduction in temporal price volatility as the penetration of VRE increase across all quantiles (50th, 75th and 90th) for 5 out of the 6 ISOs studied

(ISONE, MISO, PJM, CAISO, and NYISO). In the upper quantile (90th percentile), it is evident that at higher quantiles there is a larger reduction in temporal price volatility as VRE penetration increases indicating that there is a significant drop in higher extremes of temporal price volatility with VRE penetration. For SPP, we see that an increase in VRE percentage up to about 40% decreases the temporal price volatility; however, an increase in temporal price volatility is observed as VRE penetration increases beyond 40% up to about 60%. The difference in the effect of VRE penetration on temporal price volatility for SPP can be attributed to times of high penetration of wind when demand is low causing oversupply of electricity and, thus, increasing the frequency of negative prices. This effect observed in SPP corroborates some of the literature on price volatility where high penetration of wind can cause an increase in price volatility (*33*).

The change in the system temporal price volatility is not constant across the percentage of VRE nor the quantiles and, once again, this is typically more apparent at higher quantiles. For example, in PJM when the VRE percentage changes from 0-1% the median system temporal price volatility decreases by $0.69 USD in average absolute values and the 90th percentile of the system temporal price volatility decrease by $5.94 in average absolute values but when the VRE percentage changes from 5-6% the median system temporal price volatility decreases by about $0.17 in average absolute values and the 90% temporal price volatility decreases by about $1.24 in average absolute values. The derivative of the system temporal price volatility with respect to the percentage of VRE is depicted in *Supplementary Materials (Fig. S4)*

The result of the skew-t regression elucidates the variability of system electricity price as a function of VRE penetration. In Fig. 4, the range of the estimated skew-t distribution quantiles for detrended system price (a measure of price volatility relative to VRE) decreases as percentage of VRE increaes. The tightening of the distribution around the median price as the percentage of VRE increases is a result of the decrease in estimated skewness parameter as VRE increases. To illustrate more clearly, we present select differences in the detrended system

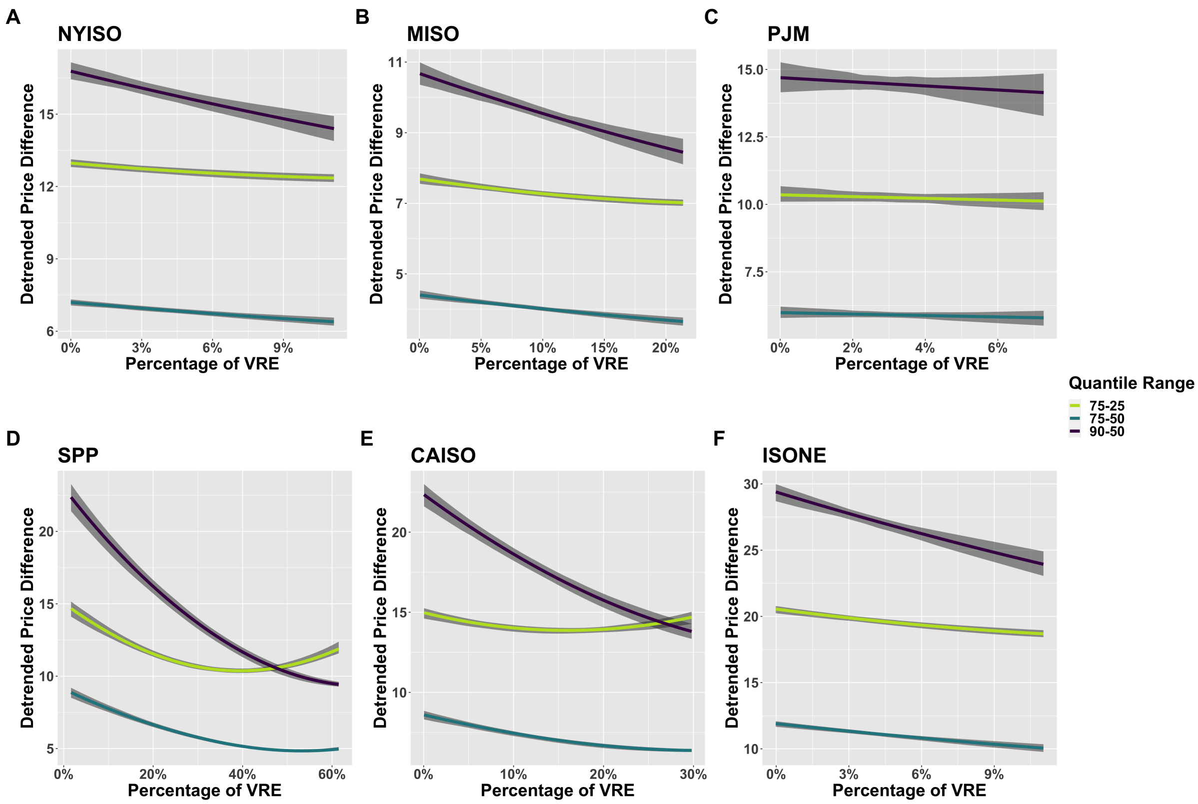

Fig. 6. Difference between $75th$ and $25th$ quantile (yellow), $75th$ and $50th$ (teal), and $90th$ and $50th$ (purple) as plotted with approximate 95% credible intervals. We note that for several of the ISOs we see decreases in the spread of the distribution (volatility with respect to VRE) in the quantiles as measured by all three differences, but SPP and CAISO have curvilinear trends in the difference between $75th$ and $25th$ which is caused by the skewness changing from positive to negative with increasing VRE penetration.

price quantiles in Fig. 6. In all ISOs studied, the detrended system electricity price difference between the 75th and 50th percentile (teal) and between the 90th and 50th percentile (purple) decrease as the percentage of VRE increases. In all but two ISOs (SPP and CAISO), a reduction in the detrended system price difference between the 75th and 25th percentile (yellow) is observed as the percentage of VRE increases. From Fig. 3, high VRE penetration leads to negative skewness in SPP and CAISO. This negative skewness effect can also be seen in Fig. 4 for the 25th quantile (yellow) with negative deviating away from the median at high VRE penetrations in SPP and CAISO. The effect is most apparent in SPP where there is high frequency of negative prices at VRE penetrations above 40%.

Overall, the reductions in these multiple measures of price volatility with respect to VRE indicate that generally increased VRE penetration reduces detrended system electricity price variability, particularly through reducing extremely high electricity prices. This trend is observed in all ISOs studied for detrended system prices above the median. The exception to this trend occurs in SPP and CAISO at high penetration of VRE for detrended system prices below the median, where there is an increased frequency of negative system prices.

Conclusion

In this study we have analyzed the relationship between system electricity price, price volatility, and VRE penetration using a robust approach to account for non-linearities and skewness. While several studies have investigated the relationship between VRE and electricity price using multivariate linear regressions, we find that these are insufficient at adequately capturing the underlying relationships in the highly skewed data. Our results not only corroborate the existing literature on the merit order effect of VRE, which causes a reduction in electricity price with increased VRE penetration, but also illustrates that the merit order effect is nonlinear and the greatest effect can be seen in the reductions in extremely high system electricity prices (90th percentile) with increased VRE. In all ISOs studied, the spread in extreme high system prices, as measured by the price difference between the 90th and 50th percentiles and the 75th and 50th percentiles, reduces as the percentage of VRE increases. In all but one ISO studied, system temporal price volatility (calculated based on the time-dependent EWMA price volatility) decreased as the penetration of VRE increased across all quantiles (50th, 75th and 90th).

Our results are consistent with the modern portfolio theory that shows that adding diverse and uncorrelated (or low correlated) assets to a portfolio results in a reduction of total price volatility. This is a particularly preferable outcome when individual assets are highly risky (i.e., individual volatilities are large), resulting in more stable and less risky portfolios of such assets.

With increasing generation from VRE on the electrical grid, the use of a robust approach helps to expose the non-linear relationships that are useful in developing an accurate understanding of behavior of system electricity price and its volatility. However, it is important to recognize that the power grid is highly dynamic and, therefore, this study should not be construed as an argument for reaching a threshold VRE penetration. The technologies, policies, and markets associated with the grid are rapidly changing. Most regions have ambitious VRE targets that will need adequate energy storage capabilities to reduce energy curtailment and negative electricity prices, innovative markets to appropriately value demand response and auxiliary services, and mindful policies to ensure that long-term infrastructure build-out meets global sustainability goals.

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Authors declare no competing interest

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Raw data and code can be found here: *https://github.com/Qunlexie/VRE-Impact-on-Price-and-Volatility*

Supplementary materials

Materials and Methods

Figs. S1 to S4

Tables S1 to S4

Supplementary Materials for
Role of Variable Renewable Energy Penetration on Electricity Price and its Volatility Across Independent System Operators in the United States

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Materials and Methods

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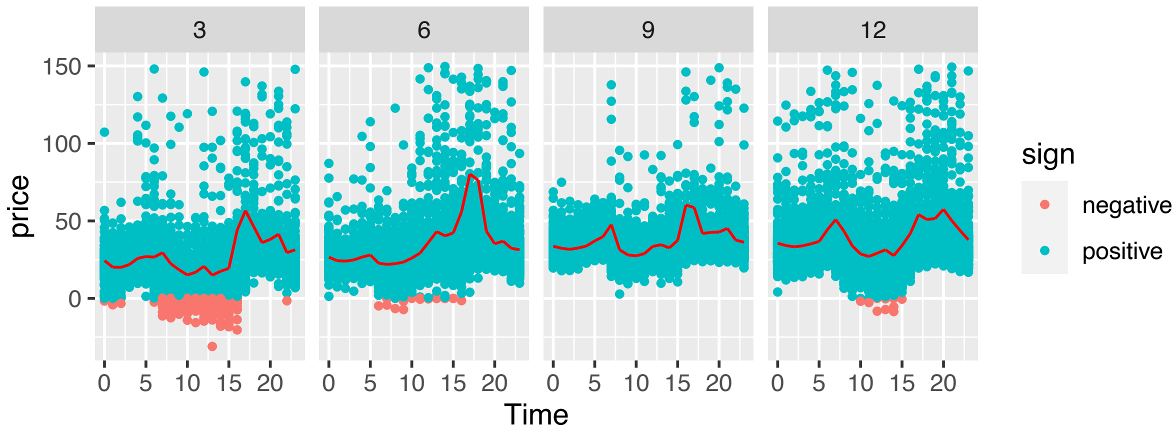

Fig. S2. CAISO prices by seasons and hour of day. The plot shows the estimated diurnal pattern (red line) by season. For plotting purposes prices greater than 150 are excluded. Orange dots depict negative prices and teal dots depict positive prices (all in $)

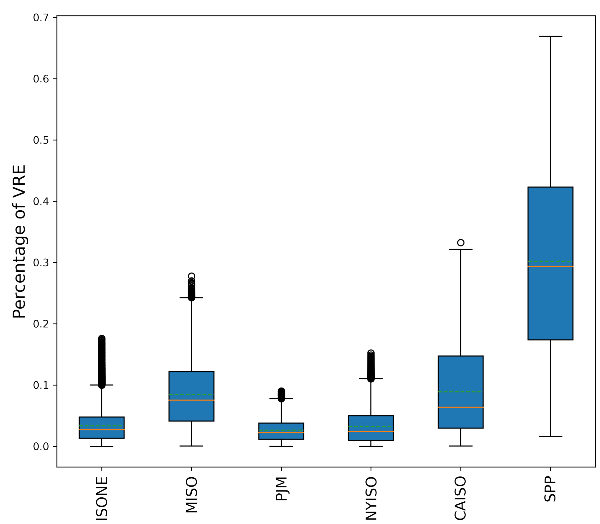

Fig. S3. Variable Renewable Energy (Solar and Wind) penetration. Shown here is the percentage of VRE generation to total generation in each of the 6 ISOs considered. Southwest Power Pool (SPP) achieved the highest VRE penetration based on the data used and for the study period considered, followed by CAISO, MISO, ISONE, NYISO and PJM.

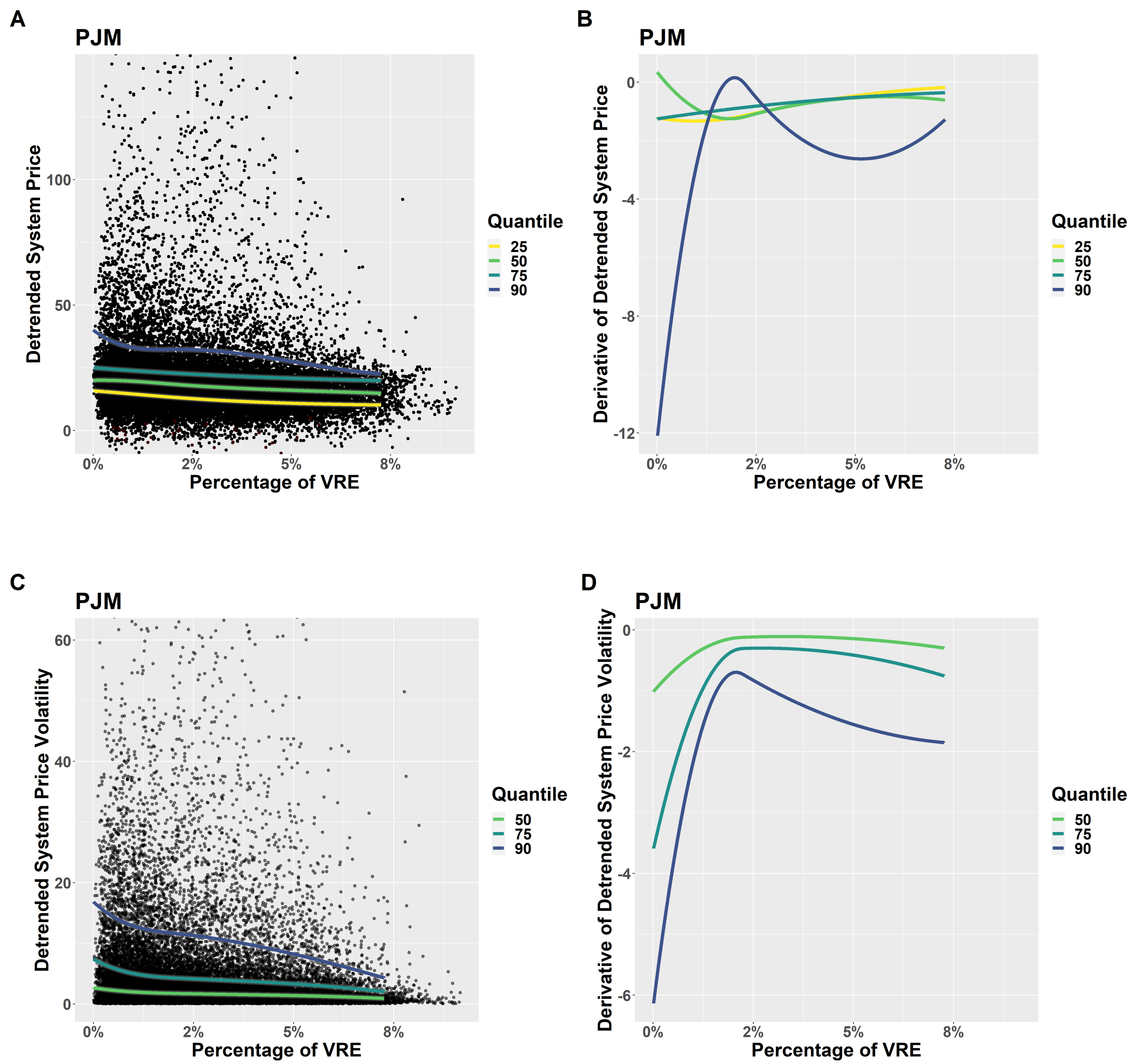

Fig. S4. The derivative of the detrended system price (in \$) and detrended system price volatility (temporal volatility in \$) with respect to the percentage of VRE for PJM Independent System Operator

Tables

Author	**Region**	**Time Period**	**Decrease in System Electricity Price per GWh of VRE**
(*Zarnikau et al., 2020*)	MISO	2013-2017	Wind (DAM): $2.1-$6
(*Bushnell and Novan, 2018*)	CAISO	2012-2016	Solar: $0.1
(*Haratyk, 2017*)	Midwest, Mid Atlantic	2008-2015	Wind (midwest): $0.612, Wind (Mid atlantic): $ 0
(*Quint and Dahlke, 2019*)	MISO	2008-2016	Wind: $1.4 - $3.4
(*Tsai and Eryilmaz, 2018*)	ERCOT	2014-2016	Wind: $1.45-$4.45
(*Zarnikau et al., 2019*)	ERCOT	2011-2017	Wind: $1.64
(*Woo et al., 2011*)	ERCOT	2007-2010	Wind (Houston):$3.9 Wind (North):$6.1 Wind (South):$3.2 Wind (West):$15.3
(*Woo et al., 2013*)	Mid-C Hub	2006-2012	Wind (Day):$0.96 Wind (Night):$0.72
(*Woo et al., 2014*)	CAISO	2010-2012	Solar (NP15):$12.4 Wind (NP15):$7.8 Solar (SP15):$12.2 Wind (SP15):$9.8 Solar (ZP26):$14.3 Wind (ZP26):$7.9
(*Woo et al., 2016*)	CAISO	2012-2015	RTM Solar (NP15):$2.2 Wind (NP15):$2.8 Solar (SP15):$3.7 Wind (SP15):$1.5 DAM Solar (NP15):$5.3 Wind (NP15):$3.3 Solar (SP15):$3.2 Wind (SP15):$1.4

Table S1. Literature summary for US studies (domestic) on VRE impact on price (note: RTM - real time market, DAM - day ahead market)

	date range	original temporal resolution - price	VRE	Reference
ISONE	2014 - 2020	hourly	Solar and Wind	(*ISONE, 2021*)
NYISO	2015 - 2020	5 mins	Wind	(*NYISO, 2020*)
PJM	2016 - 2018	hourly	Solar and Wind	(*PJM, 2021*)
MISO	2015 - 2019	hourly	Wind	(*MISO, 2021*)
SPP	2019 - 2020	5 mins	Solar and Wind	(*SPP, 2021*)
CAISO	2017 - 2020	5 mins	Solar and Wind	(*California ISO, 2017*)

Table S2. Temporal Range, References, and VRE composition for ISO data

Abbreviation	Meaning
VRE	Variable Renewable Energy
ISONE	New England Independent System Operator
NYISO	New York Independent System Operator
PJM	Pennsylvania, Jersey, Maryland Power Pool
MISO	Midcontinent Independent System Operator
SPP	Southwest Power Pool
CAISO	California Independent System Operator
API	Application Programming Interface
RTM	Real time Market
DAM	Day Ahead Market

Table S3. List of Abbreviations

ISO	parameter	Estimate	Std. Error
CAISO	β_0^μ	-5.74	0.18
	β_1^μ	-5.14	1.59
	β_0^σ	2.10	0.01
	β_0^ν	0.25	0.01
	β_1^ν	-1.58	0.11
	β_0^τ	0.52	0.01
ISONE	β_0^μ	-7.48	0.18
	β_1^μ	-62.56	4.17
	β_0^σ	2.42	0.01
	β_0^ν	0.33	0.01
	β_1^ν	-1.75	0.22
	β_0^τ	0.72	0.01
MISO	β_0^μ	-4.04	0.12
	β_1^μ	7.57	1.10
	β_0^σ	1.47	0.01
	β_0^ν	0.30	0.02
	β_1^ν	-1.07	0.14
	β_0^τ	0.78	0.01
NYISO	β_0^μ	-0.38	0.14
	β_1^μ	-98.38	3.58
	β_0^σ	2.05	0.01
	β_0^ν	0.23	0.01
	β_1^ν	-1.44	0.26
	β_0^τ	0.89	0.01
PJM	β_0^μ	-4.15	0.17
	β_1^μ	-79.23	5.13
	β_0^σ	1.74	0.01
	β_0^ν	0.33	0.02
	β_1^ν	-0.49	0.51
	β_0^τ	0.75	0.02
SPP	β_0^μ	-2.88	0.28
	β_1^μ	-5.18	0.87
	β_0^σ	1.86	0.01
	β_0^ν	0.64	0.03
	β_1^ν	-1.63	0.08
	β_0^τ	0.77	0.02

Table S4. Parameter values for the generalized skew t-distribution hourly detrended price.