Renewable Generation Capacity and Wholesale Electricity Price Variance

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ABSTRACT

The share of electric power generated from renewable energy sources such as wind and solar must increase dramatically in the coming decades if greenhouse gas emissions are to be reduced to sustainable levels. An under-researched implication of such a transition in competitive wholesale electricity markets is that greater wind and solar generation capacity directly affects wholesale price variability. In theory, two counter-vailing forces should be at work. First, greater wind and solar generation capacity should reduce short-run variance in the wholesale electricity price due to a *stochastic merit-order effect*. However, increasing the generation capacity of these technologies may increase price variance due to an *intermittency effect*. Using an instrumental variables identification strategy to control for endogeneity, we find evidence that greater combined wind and solar generation capacity is associated with an increase in the quarterly variance of wholesale electricity prices. That is, the intermittency effect dominates the stochastic merit-order effect.

Keywords: Wind power, Solar PV, Renewable energy generation capacity, Electricity price risk, Merit order, Intermittency

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1. INTRODUCTION

The transition from a global energy economy based on fossil fuels to one based on carbon-free renewable resources is among the most pressing and challenging issues of our time. As the risks of anthropogenic climate change mount, the share of electric power generated from renewable energy sources such as wind and solar photovoltaics (henceforth WPV) must increase dramatically if greenhouse gas emissions are to be reduced to sustainable levels. Around the world, the increase in WPV generation since 1990 has been significant (see Table 1). According to the International Energy Agency (IEA), in 1990 only 0.05 percent of OECD electricity generation came from WPV, but by 2012 the share had increased to 4.29 percent. This trend is expected to continue over the next 25 years. The U.S. Energy Information Administration (EIA) projects that by 2040 11.55 percent of OECD generation will come from WPV technologies. The potential impacts of such a transition on competitive wholesale electricity markets, however, are not yet fully understood.

This paper examines one such impact—the effect of greater WPV generation capacity on the short-run variation in wholesale electricity prices, a fundamental source of risk in electricity markets. Competitive wholesale electricity markets are prone to significant variability in prices, resulting from several factors including variation in fuel prices, availability of stand-by genera-

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Table 1: OECD total wind and solar PV generation (GWh): 1990, 2000, and 2012, with projection to 2040. Sources: IEA (2014a,b); EIA (2016).

Source	1990	2000	2012	2040 (proj.)
Wind	3,845	28,553	379,474	1,310,000
Solar PV	19	725	86,093	324,000
Total	**3,864**	**29,278**	**465,567**	**1,634,000**
Pct. Of total generation	**0.05**	**0.29**	**4.29**	**11.55**

tion capacity, unexpected outages, demand elasticity and exogenous demand variations, the lack of large-scale storage capability, and transmission constraints (Benini et al. 2002). This has led some researchers to label electricity as a 'paradoxical' commodity; despite being physically homogeneous at any point in time, it is heterogeneous across time because its instantaneous marginal economic value is highly variable (Hirth et al. 2016).

Large-scale penetration of WPV introduces additional variability for several reasons.[1] Although much of the variation in solar or wind generation is predictable throughout the course of a day or year, each features considerable stochasticity (Bird et al. 2013). For solar, passing clouds can cause rapid changes in the output of individual systems. Random changes in wind speeds can be problematic, but greater difficulty arises from the fact that winds typically blow stronger at night, when electricity demand is lowest. These variations affect wholesale electricity prices in a variety of ways, including altered temporal and geographic patterns, suppressed average prices in the short run, greater price volatility, and potentially negative prices (Wiser et al. 2017). Increased price variability exposes retail electricity providers to considerable wholesale price risk, which they mitigate primarily through hedging behavior.[2] Any relationship between wholesale electricity price risk and WPV generation capacity has implications for the costs of hedging and other risk management strategies faced by electric power retailers—costs that are ultimately passed on to electricity consumers.

To investigate this relationship, we have compiled an unbalanced panel of policy, price, and WPV capacity data for 19 countries over the period 2000–2011. We estimate the effect of the share of WPV in total generation capacity on the quarterly variance of daily wholesale electricity prices. One complication is that WPV capacity may be endogenous because greater price risk would likely provide a disincentive to investment; consequently, standard OLS would produce biased coefficient estimates. We therefore utilize an instrumental variables (IV) specification in which the share of WPV in total capacity is endogenously predicted by a country's policy support for these technologies. Several commonly used test statistics confirm the validity of our IV strategy. Our main finding is that a greater share of WPV in total capacity is associated with an increase in the quarterly variance of daily wholesale electricity prices. The implication is that although increased WPV generation capacity provides salient environmental benefits, it may also be associated with increased price risk in the wholesale electricity market.

To provide theoretical intuition for the empirical relationship between WPV capacity and electricity price variance, we consider two countervailing forces that are likely to emerge as WPV generation capacity is increased. In one way, greater WPV generation should suppress the variability of wholesale electricity prices in the short run. An increase in WPV shifts the electricity supply

1. See Bigerna and Bollino (2016) for a discussion of the pricing challenges to wholesale electricity markets of increased penetration of renewable energy sources. Pérez-Arriaga and Batlle (2012) discuss implications for power generation system operations.

2. Hedging typically takes the form of trading in electricity price derivatives such as forward contracts, futures, swaps, and options. A full review is not warranted here. See, for example, Tanlapco et al. (2002); Aber and Santini (2003); Vehviläinen and Keppo (2003); Deng and Oren (2006); Liu et al. (2006); Liu and Wu (2007).

curve outward, implying the stochastically fluctuating demand curve intersects it at a flatter section, reducing price variation (Johnson and Oliver 2016). We refer to this as the *stochastic merit-order effect,* an extension of the well-known *merit-order effect* of WPV generation capacity. The merit-order effect states that as long as the electricity supply curve is upward sloping (or step-wise increasing), the reduction in conventional electricity demand resulting from increased WPV capacity will reduce the spot market price of electricity. Researchers have found empirical evidence for this phenomenon in Germany (Sensfuß et al. 2008; Tveten et al. 2013; Cludius et al. 2014), Spain (Sáenz de Meira et al. 2008; Azofra et al. 2014), Italy (Clò et al. 2015), and Ontario (Rivard and Yatchew 2016).[3] In a recent paper, Hirth (2018) analyzes wholesale electricity markets in Germany and Sweden, concluding that the expansion of renewable energy has been the single most important driver of a drop in prices of nearly two-thirds over the last decade.

Conversely, stochastic price fluctuations may be compounded by the intermittency problem associated with key renewable technologies like wind and solar. An increase in intermittent generation capacity may lead to increased price variance as short-run fluctuations in WPV generation cause the electricity supply curve to shift stochastically. While improved management of these variable supplies by system operators can temper their impacts on electricity markets (Ela and O'Malley 2012; Botterud et al. 2013), recent empirical research suggests greater wind penetration typically leads to increased price volatility. Particularly when conventional generators have market power, electricity prices may be further depressed during times of excessive wind output as wind generators compete to sell excess supply, whereas conventional generators are able to increase prices further during times when wind output is low (Twomey and Neuhoff 2010).

To preview our empirical result, we find evidence of a positive, statistically significant relationship between quarterly wholesale price variance and WPV capacity, which suggests the intermittency effect dominates the stochastic merit-order effect. To our knowledge, ours is the first paper to report such a result using a multi-country panel dataset. The two papers we consider most closely related to our own find somewhat conflicting results.

Woo et al. (2011) empirically estimate the impact of wind generation capacity on intraday prices in Texas. Their primary result is the merit-order effect—greater wind generation capacity is found to reduce intraday spot prices across ERCOT's four zonal markets. These authors use their parameter estimates to compute the effect of a ten-percent increase in wind capacity on price variance. They predict increases in intraday price variance of five percent in the ERCOT-West zone and less than one percent in the other three zones, arguing that if expanded wind generation capacity has a "large impact" on electricity price variance, it may require increased use of electricity price risk-management techniques. However, it is unclear whether increases in price variance of less than one percent should be considered "large" (or economically significant), or whether the ERCOT-West zone, with a more substantial predicted price variance increase of five percent, is sufficiently representative of a normal electricity market for wider inference to be drawn.

Wozabal et al. (2014) develop a similar theoretical model to ours, examining the effect of intermittent energy sources on electricity price variance in the German power market. These authors provide a more direct test of the effects of WPV generation on price variance. Specifically, they use intraday price variance as their dependent variable (unlike Woo et al., who use price as the dependent variable and then back out predicted changes in price variance). We follow Wozabal et al. by

3. Nelson et al. (2013) examined merit-order effects related to solar feed-in tariffs in Queensland, Australia, finding the effect to be transient and not welfare enhancing. Acemoglu et al. (2017) show that when conventional generators diversify their energy portfolios via acquisition of renewable generation assets, the merit-order effect is dampened through strategic reductions in conventional power generation when renewable generation is high.

using the (log) quarterly variance in wholesale electricity prices as the dependent variable in our regressions, but follow Woo et al. in using capacity—not generation—as our key variable of inference. In contrast to Woo et al., Wozabal et al. find that increased intermittent generation generally reduces wholesale price variance, although the opposite occurs for "very low and very high" levels of intermittent generation relative to total demand (the latter being a likely explanation of the Woo et al. prediction for the ERCOT-West zone in Texas). Ultimately the effects depend on the distribution of intermittent generation and the slope of the supply function.

Given the relatively sparse literature on the relationship between electricity price variance and WPV penetration—and the apparent lack of consistency in the results of studies of single markets at the intraday level—we offer an alternative framework by testing for effects at the daily level across markets. But this is just one way to measure the relationship in which we are interested. Wholesale electricity prices vary hourly, sub-hourly, and even minute-to-minute, and hedging strategies (although not a specific focus of our analysis) take place at multiple frequencies. However, in our view finding a relationship at one frequency implies a similar relationship is likely at other frequencies. The results we present here thus have wider relevance for competitive wholesale electricity markets, generally.

The remainder of the paper proceeds as follows. In Section 2, we describe the theoretical intuition for the stochastic merit-order and intermittency effects we believe underlie the empirical relationship between WPV capacity and wholesale price variance. Section 3 describes our data and empirical design. Estimation results and discussion of implications for policy and industry are provided in Section 4. Section 5 contains several robustness checks. Section 6 concludes. Our Online Appendix provides supplementary results tables and detailed information on data sources.

2. THEORETICAL FOUNDATIONS

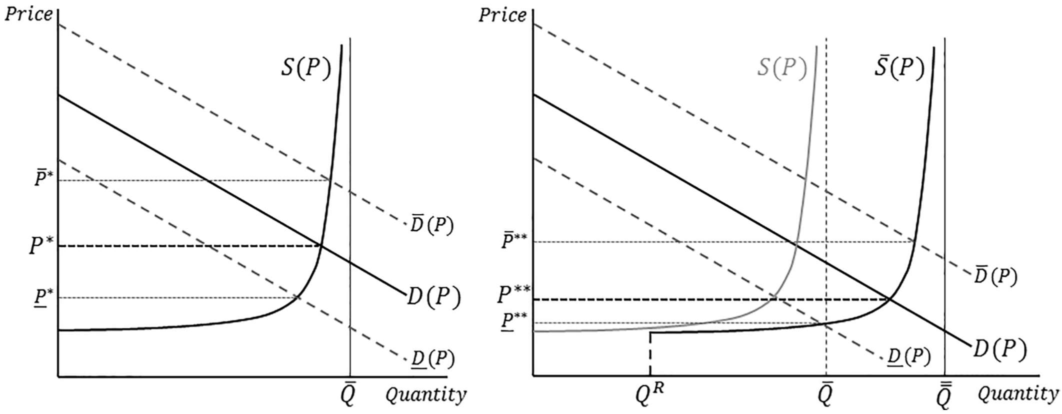
We first provide some intermediate-level microeconomic intuition for how increased WPV generation might affect short-run electricity price variation. We focus on two primary channels. The first, an outcome we call the stochastic merit-order effect, suppresses price variability. The second is an intermittency effect, which increases price variability. Although we see these two countervailing effects as occurring simultaneously, for ease of exposition we model them separately here, and rely on the empirical analysis to uncover which dominates.[4]

2.1 Stochastic Merit-Order Effect

Consider the diagrammatic model in Figure 1, which recaps the theory proposed in Johnson and Oliver (2016). Let $D(P)$ be the inverse electricity demand curve, where P is the wholesale price. Assume $D(P)$ has some stochastic component (e.g., weather related) that generates positive and negative short-run demand shocks. For simplicity, define $\bar{D}(P)$ as the upper limit for a positive demand shock and $\underline{D}(P)$ as the lower limit for a negative demand shock. Let Q denote quantity demanded/supplied. The short-run electricity supply curve, $S(P)$, is relatively flat for low quanti-

4. Long run indirect effects may also occur as conventional generating capacity is retired. However, it is unclear whether displacement of conventional plant by WPV would be one-for-one, particularly if overall demand is growing. Green and Vasilakos (2011) study the impact of increased wind generation capacity on the British power market, finding that conventional generation falls by much less than the amount of wind generation added. In a broader study, York (2012) found that over the past 50 years, each new unit of electricity generated from non-fossil fuel sources displaced on average less than one-tenth of a unit of fossil fuel generated electricity.

Figure 1: Stochastic merit-order effect: without WPV generation (left), with WPV generation (right).



ties, but rises sharply as Q approaches maximum generation capacity, $\bar{Q}$. This is consistent with the conventional wisdom concerning short-run electricity supply curves.

Panel (a) depicts the baseline scenario with no WPV. Given the upper and lower bounds of the stochastic demand curve, the equilibrium wholesale price fluctuates between $\bar{P}^*$ and $\underline{P}^*$. Even without WPV the *reverse* stochastic merit-order effect implies that as expected total electricity demand increases, marginal generation moves up the merit order, increasing price variability.

In panel (b), WPV generates amount Q^R, which we assume here is not intermittent. Under the assumption that WPV has zero marginal cost, it enters at the bottom of the merit-order—i.e., at the base of the supply curve. This shifts total supply to the right from $S(P)$ to $\bar{S}(P)$, increasing maximum generating capacity from $\bar{Q}$ to $\bar{\bar{Q}} = Q^R + \bar{Q}$. With WPV, in the absence of a demand shock the equilibrium price of electricity falls from P^* to P^{**}—the merit-order effect.[5] The range of variation in price is also lower, fluctuating between $\bar{P}^{**}$ and $\underline{P}^{**}$. This reduction in variation is the stochastic merit-order effect. We expect that any short-run increase in WPV generation should suppress variability in the wholesale price, driven by movement downward along the electricity supply curve.[6] The stochastic merit-order effect also implies negative demand shocks should lead to a greater truncation of negative price fluctuations than positive ones. This is the 'inverse leverage' effect, for which Knittel and Roberts (2005) provide empirical evidence.

2.2 Intermittency Effect

Now consider the more likely case in which WPV is intermittent, shown in Figure 2. To simplify exposition, we hold the demand curve fixed at $D(P)$. As before, panel (a) depicts the market equilibrium price without WPV, P^*. The baseline supply curve is labeled $S_0(P)$. In panel (b), we assume WPV output fluctuates between zero and some maximum value $\bar{Q}^R$, with an expected value of Q^R. The expected position of the supply curve is thus $S(P) = S_0(P) + Q^R$. Given demand, the expected equilibrium price is P^{**}. If WPV output falls to zero, the supply curve falls to $S_0(P)$

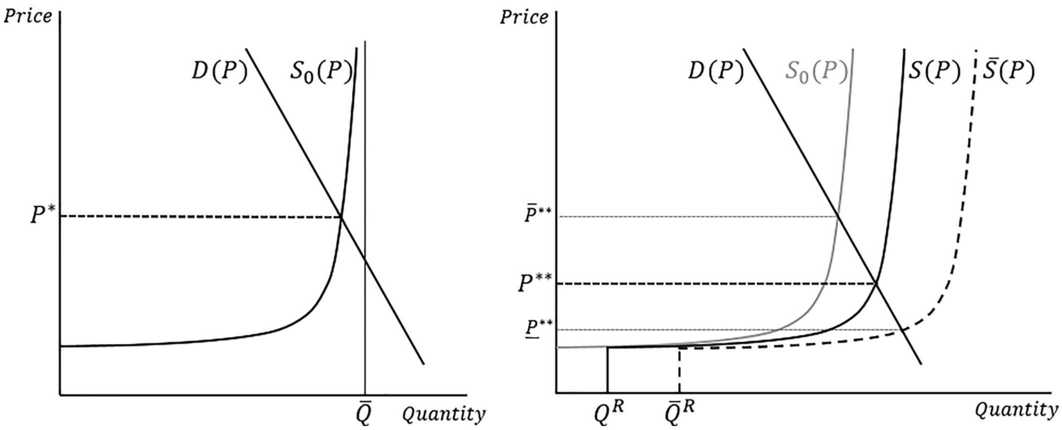
5. Although the model suggests a reduction in the equilibrium price, this does not necessarily imply a reduction in total electricity expenditures if WPV is subsidized via support policies.

6. A similar effect should emerge for any low- or zero-marginal cost generation added to the system. A new nuclear plant, for example, would cause both prices and price variability to decrease on average.

and the equilibrium price is the same as in panel (a), but is now the highest possible price with WPV, denoted $\bar{P}^{**}$. If WPV is at maximum output, supply shifts to $\bar{S}(P)$, and the equilibrium price falls to $\underline{P}^{**}$. What is clear is that the addition of intermittent WPV causes the equilibrium price to go from a stationary position to one that varies depending on WPV output. It is intuitive to extrapolate from this result that intermittency has the effect of increasing price variability relative to the no WPV case.

With these two theoretical effects in mind, we now turn our attention to an empirical examination of the net effect.

Figure 2: Intermittency effect: without WPV generation (left), with WPV generation (right).



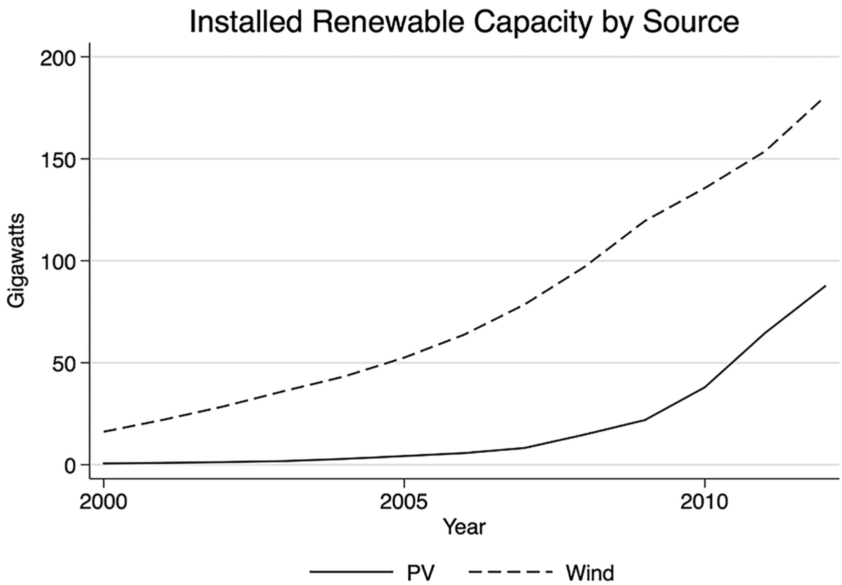
3. EMPIRICAL ANALYSIS

When describing a stochastic economic outcome like wholesale electricity prices, variance is, in every practical sense, synonymous with risk. Our dependent variable is the quarterly variance in daily electricity prices at the country level. Denoting the wholesale electricity price as $P_{i,t}$ for country *i* on day *t*, we compute $V_{i,s} \equiv var\left[P_{i,t\in s}\right]$, where *s* indexes quarter. For our main specification, we take the natural logs of $V_{i,s}$ and of all relevant covariates, but as a robustness check we present additional models in which all data are in levels.

Our final sample consists of an unbalanced panel of 19 countries over the period 2000–2011 with varied amounts of WPV capacity, both in absolute terms and relative to the size of the market. Our data were compiled from multiple sources, requiring a formidable data-cleaning process. The reward is that our dataset is entirely unique to this paper. A detailed guide to our data sources is provided in the Online Appendix. Our choice to use WPV capacity—as opposed to generation—is based on data availability. We simply do not have the requisite data needed to construct an accurate measure of quarterly WPV generation across countries. As an additional robustness check we construct a noisy estimate of WPV generation and find no evidence to suggest that using capacity instead of generation leads to economically significant differences in the overall results (see Section 5.4).

Daily and/or hourly wholesale prices and total generation data were in some cases publicly available (e.g., Australia and New Zealand), but most were purchased from Platts McGraw-Hill (EU and UK) and NordPool Spot (Scandinavian countries). We use spot prices where available. Otherwise, we use day-ahead prices. For many countries, separate peak and off-peak prices were avail-

Figure 3: Sample total wind and solar PV generation capacities.



able. In such cases we created a daily weighted-average price—that is, weighted by the fraction of hours in the peak- and off-peak periods. For countries whose wholesale price data were recorded at sub-daily intervals, we computed a quantity-weighted average price for each day. We used a similar method when multiple market nodes were available.[7] All prices are converted to constant 2010 US dollars.[8] Daily price indices were not available for all countries in our sample over the full sample period, hence the use of an unbalanced panel. Due to data availability, our data for the United States is limited to the Northeast U.S. (New York ISO, ISO New England, and PJM), which encompasses a large share of the state-level renewable portfolio standard requirements in the U.S.[9] Similarly, our data for Canada is limited to Ontario. While we would prefer to have larger shares of the U.S. and Canadian markets, we see these data limitations as having little impact on our analysis.

Wind generation capacity data were publicly available via the Global Wind Energy Council. Solar generation capacity data were purchased from the European Photovoltaic Industry Association; this measure includes both utility-scale and 'behind-the-meter' capacity. Both datasets included data for our full sample of countries over the entire sample period. Figure 3 presents total installed WPV generation across our sample countries. Wind capacity dominates, and has increased dramatically over the sample period from less than 20 GW in 2000 to nearly 175 GW by 2012. Solar generation capacity is negligible until around 2005, but increased to roughly 90 GW by 2012. For the remainder of our analysis, we transform WPV capacities into the combined share of WPV in total capacity, denoted $wpv\_share_{i,s}$, the rationale being that a GW of WPV capacity will likely

7. This was the case for the NordPool countries. Platts country-level daily price data are already computed as spatially and temporally weighted averages.

8. We use monthly market exchange rates and annual GDP deflators for each country. Exchange rates are from the Federal Reserve Economic Data (FRED) database of the St. Louis Fed. GDP deflator data are from the World Bank Development Indicators database.

9. Renewable portfolio standards are policies that require a legislatively defined fraction of electricity sales to come from renewable electricity sources, usually wind and solar PV. A more complete explanation follows in Section 3.2.

have a different impact on price variation depending on the overall size of the market.[10] This share is expressed on a scale of 0–100 percent (rather than 0–1), simplifying interpretation of estimated marginal effects. Total generation capacity data for all countries in our sample were acquired from the EIA.

Figure 4 contains separate scatterplots of log quarterly price variance, $\ln\left(V_{i,s}\right)$, against $wpv\_share_{i.s}$ for each country. These scatterplots of the unconditional data reveal that in some countries—e.g., Sweden and New Zealand—the relationship appears strongly positive. However, in others—e.g., Belgium, France, and Germany—the relationship appears negative. For yet others like Spain or Denmark, there is no visibly obvious relationship. Because these data are unconditional, it is unclear at this point whether these contrasts reflect variation across countries in other factors relevant to price variation or if there is simply no systematic relationship between price variance and WPV capacity. A third possibility is that, given the countervailing nature of the stochastic merit-order and intermittency effects, the former dominates in some countries and the latter in others. Figure 4 provides motivation for our regression analysis to reveal deeper insight.

Table 2 presents summary statistics for daily prices, quarterly price variance, total capacity, and WPV capacity shares, and for our quarterly and annual control variables and instrumental variables (explained below). In our Online Appendix (Table A1) we present the results of unit root tests for all variables. Given the unbalanced panel structure of our data, the p-values presented are from a Fisher-type test with the null hypothesis that all panels in the data have a unit root and the alternative that at least one panel does not have a unit root. We reject the null hypothesis for all but one variable, leaving us cautiously optimistic that our specification avoids spurious regression problems.[11]

3.1 Main Regression Equation

We employ an IV identification strategy in which the share of WPV in total capacity is treated as endogenous. We estimate the following regression equation:

$$\ln\left(V_{i,s}\right) = \beta \cdot wpv\_share_{i.s} + \boldsymbol{X}'_{i,s}\boldsymbol{\delta} + \alpha_i + \theta_s + \gamma_y + \varepsilon_{i,s}, \tag{1}$$

where $X_{i,s}$ is a vector of quarterly control variables, α_i are country fixed effects, θ_s are quarterly fixed effects,[12] γ_y are year fixed effects, and $\varepsilon_{i,s}$ is the error term. We expect longer term variation in electricity prices not due to stochastic daily phenomena to be picked up by these fixed effects. For example, hydropower generation in most countries stays largely constant within our sample period but may fluctuate seasonally based on precipitation and snowmelt patterns, affecting prices. Likewise, a country's grid interconnectivity with neighboring countries—and thus the potential for importing and exporting electric power, which could affect price variance locally—is likely to stay roughly constant over our sample period.

Our control variables are as follows. First, we include total electricity generation, constructed as the sum of daily/hourly generation within country i in quarter s. We expect the coefficient on total generation to be positive, which we earlier noted is indicative of a *reverse* stochastic merit-order effect. Second, because natural gas (predominantly) and oil are typically used as the marginal fuels in electricity generation, the contemporaneous variation in their market prices should affect variation in the wholesale electricity price. We use quarterly variances of daily Brent crude

10. Using shares also accounts for any retirements of conventional generating capacity.

11. The p-value for the one variable that does not pass at conventional levels of confidence is marginal at 0.102.

12. More accurately, θ_s are seasonal fixed effects—we switch Q1-Q3 and Q2-Q4 for southern hemisphere countries.

Figure 4: Scatterplots by country of log quarterly price variance against combined share of WPV in total generation capacity.

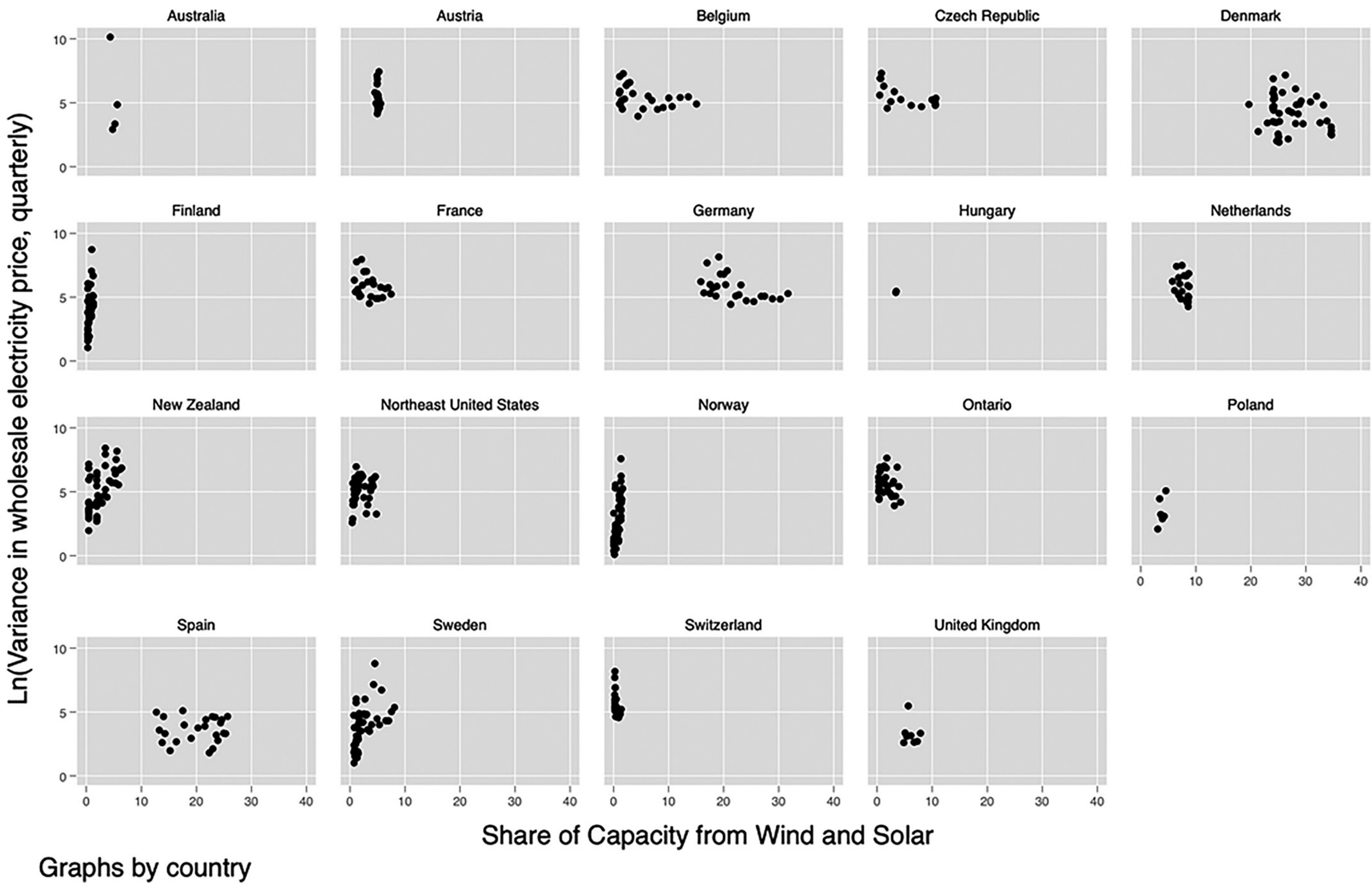


Table 2: Panel summary statistics.

Variable	Mean	Std. Dev.	Min.	Max.
Daily wholesale electricity price (USD/MWh)	53.65	32.00	–0.72	1,030.72
Quarterly variables				
Variance, wholesale electricity price (USD/MWh)	358.16	1,268.31	1.10	25,424.79
Total capacity (GW)	118.36	256.66	7.85	1,051.25
WPV cumulative capacity (GW)	5.01	9.87	0.01	53.09
Share of WPV in total capacity (0–100)	6.61	8.83	0.05	34.68
Total electricity generation (GWh)	1.20×10^{8}	2.65×10^{8}	3,132,559	1.19×10^{9}
Variance, Henry Hub NG price (USD/MMBtu)	54.01	79.00	0.72	341.74
Variance, Brent crude oil price (USD/barrel)	101.40	174.08	0.25	759.33
Variance, Daily maximum temperature (°C)	17.68	11.07	0.10	65.83
Variance, Daily minimum temperature (°C)	15.04	10.68	0.38	68.35
Annual variables				
Population (millions)	41.29	78.60	3.86	311.58
GDP (trillions, 2014 USD)	1.77	3.57	0.05	15.53
CO_2 emissions by electricity sector (millions of metric tons)	269.92	704.31	3.69	2,760.36
Instrumental variables (quarterly)				
Fraction of obs. with RPS	0.18	-	-	-
Fraction of obs. with Wind FIT	0.43	-	-	-
Fraction of obs. with PV FIT	0.45	-	-	-
Fraction of obs. with either Wind or PV FIT	0.46	-	-	-
RPS requirement (percentage)	1.76	4.08	0	18.2
FIT payment to Wind (USD/MWh)	46.69	65.90	0	334.38
FIT payment to Solar PV (USD/MWh)	176.73	250.27	0	881.11
Kyoto ratification	0.84	0.36	0	1

NOTE: (i) Total number of daily wholesale price observations is 46,857. (ii) Total number of quarterly observations is 520. (ii) All monetary values expressed in constant 2010 USD, unless otherwise noted.

and Henry Hub natural gas spot prices, which we consider reasonable global benchmark prices for each resource. Potential socio-economic effects related to economy size and population are captured by including real GDP and population, each at an annual level. To control for possible effects related to other carbon emissions reduction policies—e.g., emissions trading schemes—we include annual CO_2 emissions generated by the electricity sector. Finally, we control for the effects of temperature-related demand shocks by including the quarterly variance in country *i*'s daily maximum and minimum temperatures.[13]

3.2 Instrumental Variables Strategy

Our underlying motivation for utilizing an IV identification strategy is that WPV generation capacity is likely to be endogenous to price variance because the associated risk would presumably create a disincentive to investment. Capital investment in WPV technologies requires large up-front fixed costs. In markets where prices are highly variable for reasons *other than* the share of WPV in total capacity, investment in WPV is likely to be lower. Investors will be more cautious when price (and, consequently, revenue) risk is greater, because of the greater uncertainty with respect to cost recovery. Using OLS to estimate (1) would bias estimates of the effect of WPV capacity on wholesale price variance downward. Another potential source of bias in our model relates to

13. Daily maximum and minimum temperature data are in degrees Celsius, and for each country are calculated as a national-level average across weather stations. Collected from NOAA (Menne et al. 2012a, b).

unobserved heterogeneity in several factors (omitted variables) that may affect price variance, like economies of scale, discount rates, risk aversion, technical ability, weather conditions, wind speeds, solar radiation, or "green preferences". Our model includes panel fixed effects to capture much of this unobserved variation, but not all.[14]

The IV approach addresses these issues by exploiting the exogenous variation in one or more instrumental variables that are correlated with $wpv\_share_{i,s}$. The IV strategy is empirically valid if and only if the IV's are independent of the main outcome variable and jointly uncorrelated with the error term. This eliminates simultaneity and/or omitted variables bias precisely because the IV estimator uses only the variation in $wpv\_share_{i,s}$ correlated with exogenous variation in the instrument(s) to compute the coefficient estimate of interest.

Our primary choice of instrumentation uses various aspects of countries' policy support for WPV generation. Many governments have implemented economic support policies to stimulate investment in generation from WPV and other renewables, with the goal of reducing carbon emissions. Two dominant renewable support policies have emerged—feed-in tariffs (FIT) and renewable portfolio standards (RPS).

Our preferred instrumentation utilizes the one-year change in the natural logs of the FITs paid to PV and wind. FIT supports investment in renewable generation in two ways.[15] First, it guarantees eligible producers receive a fixed price per kWh or the spot price plus a fixed premium (Cory et al. 2009). Second, the nearest utility provider is obligated to purchase and distribute all renewable energy that 'feeds-in' to the grid, regardless of electricity demand (Mendonça et al. 2010).[16]

We expect the relationship between FIT remuneration levels and WPV share to be negative for two reasons. First, most FITs provide for tariff digression, where the level of remuneration depends on a plant's vintage—newer plants receive lower guaranteed payments, increasing the incentive to install new capacity sooner rather than later and stimulating technological improvement. Figures A1 and A2 of the Online Appendix plot, respectively, PV and wind FITs for individual countries over time. For most countries, PV FITs are declining over most of the sample. Wind FITs, by contrast, appear to be mostly increasing over time. This would seem to contradict the tariff digression feature. The obvious explanation for this is site heterogeneity. FIT remuneration levels are set based on levelized cost, and the most productive sites—i.e., those that operate at the lowest levelized cost per kWh (due to greater consistency in wind speeds)—are selected first. Over time, less suitable sites are selected, which operate at a higher levelized cost, requiring a higher remuneration level.

The second reason we expect a negative relationship between FIT remuneration levels and WPV share—particularly for wind—is economies of scale in wind production (Blanco 2009). Countries with a higher WPV share—made up of mostly wind—are more likely to have achieved economies of scale in wind generation, implying a lower levelized cost per kWh and thus a lower FIT remuneration level. Evidence of this negative relationship across countries is seen clearly via a pooled, unconditional scatter plot of FIT remuneration levels against WPV share (Online Appendix,

14. A third source of potential endogeneity might be mismeasurement of WPV capacity that is systematically correlated with observables, but we have no reason to suspect this is an issue in our data.

15. Mendonça et al. (2010) provide a complete overview. A more concise review is available in Couture and Gagnon (2010).

16. Tariff levels are typically based on levelized cost-of-service (Couture and Cory 2009). Total generation costs per kWh vary across technologies and sites, and include the costs of capital investment, regulatory compliance and licensing, operation and maintenance, fuel costs (for biomass and biogas), inflation and interest, and a rate of return on investment (Klein et al. 2010). The most commonly used remuneration period is 15–20 years, where 20 years is considered the average life of a typical renewable energy plant (Mendonça et al. 2010).

Figure A3). Importantly, this variation would not be picked up by country fixed effects, because it is not time-invariant. A similar relationship appears to hold for PV FITs (Figure A4).

RPS is a quantity-based instrument in which the regulator requires that a specified minimum proportion of electricity come from renewable sources (typically per year). Electric utilities can meet RPS requirements by purchasing renewable energy from independent generators, or through installation and operation of their own facilities (Wiser et al. 2005).[17] Naturally, we expect the relationship between the RPS percentage requirement and WPV share to be positive.

The primary threat to the validity of our instruments is the possibility that policy makers may choose FIT or RPS policies with the specific purpose of managing electricity price volatility. If true, this policy endogeneity would undermine our IV strategy, as it would violate the exclusion restriction. In our view, cross-country differences in price variance are unlikely to be driving the variation in FIT/RPS policy.[18] Stated justifications for most renewable support policies are to increase the amount of renewables in the electricity production system and to reduce both global and local pollution from fossil fuel generation. Moreover, there are likely simpler and more effective policies to reduce electricity price volatility than FIT or RPS, such as implementing large-scale demand-side management and energy efficiency programs.

However, if policy makers do have price volatility in mind when choosing FIT/RPS policy, then it should be that countries that eventually adopt such policies have higher electricity price variance than countries that do not. To test this hypothesis, we constructed a subsample of our data including only observations for which a given country *did not* have a FIT/RPS policy in place. We then regressed price variance on an indicator variable that takes the value "1" if the country *ever* passed a FIT/RPS policy, and "0" if the country never implemented either policy. This provides a lens for us to examine whether countries that went on to pass FIT/RPS policies were different in terms of electricity price variance than those that did not. The results of these regressions are available in our Online Appendix (Table A2). We find no statistically significant evidence that the quarterly variance in electricity prices differed across these two sets of countries, plausibly alleviating the concern that the policies themselves were endogenously selected based on differences in price variance.[19]

FIT and RPS data are taken from an updated version of the dataset used in Johnstone et al. (2010) and contain FIT payments (by resource) and RPS requirements for each country at an annual interval. Figure 5 displays average FIT payments by resource by year across our sample and RPS percentage requirements by country by year. FIT is the dominant policy, with 46 percent of country-quarters having an active FIT for either technology, in contrast to only 18 percent of country-quarters with an RPS (see Table 2). Moreover, FIT payments are substantially different across these two technologies, reflecting differing costs. The average FIT payment for wind, one of the

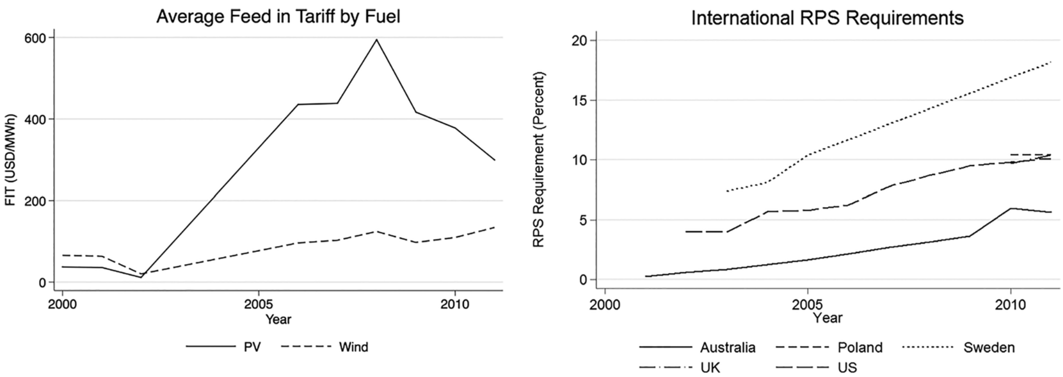
17. RPS policy typically includes a complementary market for renewable energy certificates (RECs). For every MWh of renewable energy generated, a REC is created. The utility pays the renewable generator for both the electricity supplied and the REC, in effect subsidizing renewable energy. Each year, RECs are surrendered to the jurisdictional regulator to demonstrate compliance with the RPS. Utilities with RECs in excess of the RPS requirement can sell them, while others might purchase RECs as a substitute for purchasing electricity directly from renewable generators (Wiser and Barbose 2008). RECs may also be 'banked' for future use (Johnson 2014). See Amundsen and Mortensen (2001) for formal analytical treatment.

18. Upton and Snyder (2015) identify variation in wind and solar potential as a statistically significant driver of RPS policy adoption across U.S. states. Their analysis controls for several political and economic variables, but does not include wholesale price variation as an explanatory variable.

19. Our sample is limited in this exercise, because some countries had a policy in place over the entirety of our observation period.

cheaper renewable fuels, is \$0.05/KWh, whereas the average FIT payment for solar PV, one of the most expensive, is \$0.18/KWh.

Figure 5: Sample average FIT by fuel (left) and sample RPS requirements (right).



Our first-stage estimation equation is

$$wpv\_share_{i.s} = \boldsymbol{Z}'_{i,s}\xi + \boldsymbol{X}'_{i,s}\boldsymbol{\eta} + \omega_i + \varphi_s + \tau_y + \mu_{i,s}, \tag{2}$$

where $\boldsymbol{Z}'_{i,s}$ is the vector of instrumental variables, $\boldsymbol{X}'_{i,s}$ is the vector of covariates not excluded from the second stage (described earlier), ω_i are country fixed effects, φ_s are quarterly fixed effects, and τ_y are year fixed effects. As in the second stage, we use heteroscedasticity-robust standard errors, clustered by country group-year.

Table 3 presents our first-stage OLS estimates. Along with a variety of alternative combinations of non-excluded controls, our instruments explain the variation in WPV capacity shares quite robustly, with point estimates that remain relatively stable across models. In each model, the coefficient estimate for the RPS percentage requirement is positive and highly significant. Interpretation of this coefficient is straightforward—a one percentage-point increase in the RPS requirement leads to a 0.14–0.15 percentage point increase in the share of WPV in total capacity. This is intuitive, as WPV makes up only a fraction of installed capacity from resources that are typically eligible under RPS requirements, which include geothermal, biomass, ocean/tidal, and both large- and small-scale hydro power. Moreover, in some cases an RPS may be non-binding and therefore may not directly stimulate new investment in renewables (Shrimali and Kniefel 2011).[20] As expected, the point estimate on the one-year change in FIT payments to wind is negative and strongly significant. The one-year change in FITs paid to PV is not statistically significant, likely due to small shares of total generation coming from solar in most countries.

Total electricity generation—a non-excluded variable—appears positively related to the share of WPV in total capacity, but is not statistically significant. We find a consistently negative, significant relationship between GDP and $wpv\_share_{i.s}$. We interpret this as reflecting a causal relationship that likely goes in the other direction; intuitively, greater WPV penetration would generally lead to higher energy costs overall, negatively impacting GDP. Conversely, we find a positive, significant relationship between a country's population and its WPV share. This may simply reflect

20. For example, say an RPS requirement of 10 percent is implemented in a country that already generates 12 percent of its supply from eligible renewable sources. The RPS would be non-binding, because no new renewable generation would be needed to meet the requirement.

Table 3: First-stage OLS estimates. Dependent variable: $wpv\_share_{i,s}$.

	(1)	(2)	(3)
Excluded instruments:			
RPS percent requirement	0.14***	0.14***	0.15***
	(0.05)	(0.05)	(0.05)
ΔLn(PV_FIT)	0.01	–0.01	–0.00
	(0.15)	(0.14)	(0.14)
ΔLn(wind_FIT)	–0.72***	–0.65***	–0.64***
	(0.14)	(0.15)	(0.14)
Other covariates:			
Ln(total electricity generation)	1.15	0.96	1.39
	(1.09)	(0.97)	(1.15)
Ln(variance, Henry Hub NG price)	–0.02	–0.02	–0.04
	(0.04)	(0.04)	(0.05)
Ln(variance, Brent crude oil price)	–0.05	–0.05	–0.08
	(0.05)	(0.05)	(0.06)
Ln(GDP)		–4.17*	–3.84*
		(2.09)	(2.04)
Ln(population)		41.87***	38.32**
		(16.67)	(16.54)
Ln(CO_2 emissions from electricity sector)		–1.56	–1.66
		(1.52)	(1.52)
Ln(variance, maximum daily temperature)			0.52**
			(0.24)
Ln(variance, minimum daily temperature)			–0.13
			(0.22)
Number observations	446	446	446
R^2	0.97	0.97	0.97

NOTES: (i) All models include country, year, and quarter fixed effects with robust standard errors clustered by country group-year. (ii) *p<0.10, ** p<0.05, *** p<0.01

the contemporaneous growth of both population and WPV investment over time. Finally, we find no relationship between WPV shares and the quarterly variances of either natural gas or crude oil prices, and only limited evidence that WPV shares are related to temperature variances.

In our Online Appendix (Tables A3 and A4), as a robustness check we report similar models with a slightly different instrumentation. Instead of using the one-year change in the natural logs of FITs paid to PV and wind, we use contemporaneous logged values, and add the year of ratification of the Kyoto Protocol as an additional instrument.[21] This yields slightly better first stage results in terms of statistical significance of coefficient estimates, but we consider the specification inferior to the instrumentation presented in Table 3 based on several IV diagnostic test statistics discussed below.

4. MAIN RESULTS

Table 4 presents the coefficient estimates for our main regression equation. Columns (1)-(3) present OLS estimates. Columns (4)-(6) present evidence from IV regression specifications corresponding respectively to the first-stage regressions in Table 3. In all regressions standard errors are heteroscedasticity-robust, clustered by country group-year, for a total of 51 clusters. This satisfies the rule of thumb of at least 50 clusters to avoid over-rejection in group-year panel data models

21. Both Aichele and Felbermayr (2012) and Cifci and Oliver (2018) find evidence that countries' participation in the Kyoto Protocol significantly reduced CO_2 emissions. A natural conclusion is that much of these emissions reductions were achieved via increasing the shares of WPV in total generation.

(Cameron and Miller 2014). Country groups are based on geographic adjacency and relative integration of electricity markets. NordPool countries comprise one country group, whereas continental European Union countries (Spain excluded) form another. Northeast U.S., Ontario, Australia, New Zealand, Spain, and UK each comprise single-country groups.

4.1 OLS Estimates

The OLS estimates suggest the relationship between the share of WPV in total capacity and quarterly wholesale price variance is negative and statistically significant at the 5% level. This result suggests the stochastic merit-order effect of greater WPV penetration dominates the intermittency effect. The coefficient estimates in columns (2) and (3) indicate a 1 percentage-point increase in the WPV share is associated with a reduction in $\ln\left(V_{i,s}\right)$ of 0.06. To get a sense of magnitude, the sample mean of quarterly wholesale price variance is 358.16 (see Table 2), which, taking the square root, yields a quarterly standard deviation of \$18.92/MWh. A 0.06 reduction in $\ln\left(V_{i,s}\right)$ corresponds to a reduction in quarterly price variance of roughly 5.5 percent to 338.30, and a reduction in standard deviation of roughly 3 percent to \$18.37 USD/MWh.

Also providing evidence for the existence of a stochastic merit-order effect—albeit in the opposite direction—is the positive significant coefficient estimate on total electricity generation in columns (1) and (2). As total quantity generated increases, intuitively we can infer that the intersection of the demand and supply curves moves up along the steeper portion of the supply curve. When daily demand fluctuates, the resulting price variation is therefore greater. These estimates can be interpreted as pure elasticities—as both dependent and independent variables are in logs—indicating a 1 percent increase in total electricity generation is associated with a slightly greater than 1 percent increase in quarterly price variance.

4.2 IV Estimates

Utilizing an IV specification yields a striking result when compared to OLS—in each IV model the effect of WPV share on quarterly price variance is *positive* and statistically significant at 95% confidence or better. This result suggests it is, in fact, the intermittency effect that dominates the stochastic merit-order effect as the share of WPV in total generation capacity is increased. Our IV estimates of the effect of a one percentage-point increase in WPV share on (log) quarterly price variance range between 0.1 and 0.12. Again, starting from the sample mean of 358.16 (standard deviation \$18.92/MWh), this corresponds to an increase in quarterly price variance of 10.5–12.7 percent to between 395.83 (standard deviation \$19.90/MWh) and 403.82 (standard deviation \$20.10/MWh). These are non-trivial increases, implying the distribution of prices widens considerably as a result of increased WPV penetration.

These results also suggest the endogeneity bias inherent in the OLS estimates is overwhelming the true effect of WPV penetration on wholesale price variance to such a degree that it pushes the estimates beyond the zero. Because higher price variance presents a disincentive to invest in these technologies, we should expect countries with higher price variance to have a lower share of WPV. Our IV models indicate the resulting bias is so strong that OLS estimates come out negative and significant, making it appear as if the effect of WPV share on price variance is negative. The IV strategy eliminates this endogeneity bias, and the true effect is revealed to be positive.

We report several commonly used test statistics that confirm the validity of our IV strategy. First, the p-values for a first-stage F-test of our excluded instruments confirms joint significance in the first stage. Second, we report p-values for the Kleibergen-Paap *rk* LM statistic, which indicates

Table 4: OLS and second-stage IV estimates of Eq. (1). Dependent variable: ln($V_{i,s}$).

	(1)	(2)	(3)	(4)	(5)	(6)
WPV share	–0.05**	–0.06**	–0.06**	0.10***	0.12**	0.12**
	(0.03)	(0.02)	(0.02)	(0.04)	(0.05)	(0.05)
Ln(total electricity generation)	1.13**	1.08*	0.81	1.60*	1.60*	1.06
	(0.54)	(0.55)	(0.51)	(0.85)	(0.85)	(0.83)
Ln(variance, Henry Hub NG	0.13	0.13	0.13	0.28***	0.28***	0.28***
price)	(0.13)	(0.13)	(0.13)	(0.09)	(0.09)	(0.09)
Ln(variance, Brent crude oil	0.07	0.07	0.09	0.07	0.07	0.08
price)	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)	(0.10)
Ln(GDP)		–0.07	0.01		0.92	1.11
		(0.82)	(0.88)		(1.23)	(1.25)
Ln(population)		4.71	3.93		–9.22	–10.95
		(6.74)	(7.11)		(11.57)	(12.03)
Ln(CO_2 emissions from		0.47	0.45		0.85	0.83
electricity sector)		(0.99)	(0.97)		(1.03)	(1.01)
Ln(variance, maximum daily			0.44*			–0.30
temperature)			(0.24)			(0.23)
Ln(variance, minimum daily			–0.30			0.45*
temperature)			(0.22)			(0.23)
Specification	OLS	OLS	OLS	IV	IV	IV
Observations	520	520	520	446	446	446
R^2	0.59	0.59	0.59	0.57	0.56	0.56
IV diagnostics						
First-stage F-test of excluded instruments (p-value)				0.00	0.00	0.00
Weak instrument robust inference (Andersen-Rubin χ^2, p-value)				0.01	0.03	0.03
Under-identification (Kleibergen-Papp rank LM F-stat, p-value)				0.09	0.08	0.08
Over-identification (Hansen's J, p-value)				0.72	0.61	0.66
Weak identification (Cragg-Donald Wald F-stat)				30.25	24.78	24.91
Stock-Yogo critical value: 10% max. F-stat size bias				22.30	22.30	22.30
Stock-Yogo critical value: 5% max. bias relative to OLS				13.91	13.91	13.91

NOTES: (i) IV specifications in columns (4)-(6) correspond to first-stage regressions in Table 3, models (1)-(3), respectively. (ii) All models include country, year, and quarter fixed effects with robust standard errors clustered by country group-year. (iii) * p<0.10, ** p<0.05, *** p<0.01

that for all models we reject the null hypothesis of under-identification at 90% confidence or better. Third, Hansen's J is a test of over-identifying restrictions. Failure to reject the null is the preferred outcome for this test, which indicates whether the restrictions implied by the existence of more instruments than endogenous regressors are valid. For all IV models, we are unable to reject the null. Fourth, we report the Cragg-Donald Wald *F*-statistic, along with the Stock-Yogo critical values for the maximal bias of IV estimation, both for the size of the Wald test and for the size of the bias of the IV estimator relative to the bias of the OLS estimator. The interpretation is that the instruments are weak if the Cragg-Donald Wald F does not exceed these critical values. We also report the *p*-values for an Andersen-Rubin χ^2 statistic that tests for weak-instrument robust inference. The null hypothesis here, which we reject at better than 95% confidence in all models, is that the coefficients of the endogenous regressors in the structural equation are jointly equal to zero and that the over-identifying restrictions are valid, where the test itself is robust to weak instruments.

As noted earlier, in our Online Appendix we report the results of an alternative IV specification (see Tables A3 and A4). The key results are consistent with those presented in Tables 3 and 4, and serve as an additional robustness check. However, minor issues arise with this choice of instrumentation. First, the Hansen's J statistics are either marginal or allow us to reject the null at 90% confidence. Second, in two models the Cragg-Donald Wald F falls short of the Stock-Yogo critical value for a 10% maximal size bias, alerting us to the possibility of weak instruments.[22] Based on these IV diagnostic tests, we feel the models reported above in Tables 3 and 4 are objectively superior, and thus represent our preferred specification.

In any case, the key implication is that dramatically increasing the share of intermittent technologies like wind and solar in total generation capacity—as EIA projections indicate is probable over the next two decades—may be associated with significant increases in wholesale electricity price variance and, therefore, risk. This increase in short-run price risk from the intermittency effect of WPV is likely to lead to higher risk premiums passed on to electricity consumers and greater resources devoted to risk management strategies such as hedging and futures trading, in addition to the potentially higher costs of the technologies themselves.

A second, subtler implication relates to economic welfare and the costs of meeting peak demand. Our result suggests that as the share of WPV in total capacity increases, the most expensive 'peaker' plants—i.e., those at the steepest section of the conventional electricity supply curve—are more likely to be needed in the event of an unusually intense negative intermittent supply shock. Greater WPV penetration exacerbates the transfer of economic surplus from consumers to producers when such supply shocks occur in a competitive power market regime. Suppliers capture greater windfall profits, because negative supply shocks result in concomitant wholesale price shocks that are more severe than they might otherwise be.

Examining the other covariates, models (4) and (5) indicate—similarly to OLS—that an increase in total generation increases price variance, as expected. In model (6), which adds to the specification the (log) variances in daily minimum and maximum temperatures, the estimated effect of total generation remains positive but is not statistically significant at 90 percent (*p*-value 0.20). Unsurprisingly, the quarterly variance of natural gas prices is strongly related to the variance of wholesale electricity prices, whereas annual-level GDP, population, and CO_2 emissions appear unrelated. In model (6) the evidence for any relationship between the quarterly variance in daily temperatures and price variance is mixed—only the variance in minimum temperatures is statistically significant at 90 percent. This is likely because most countries in our sample—the U.S. being the exception—overwhelmingly utilize electric power for space heating instead of natural gas, but do not widely use air-conditioning during summer months.

5. ROBUSTNESS CHECKS

We explore several categories of additional robustness checks. The results of each provide further evidence in support of our main finding—that the intermittency effect of greater WPV penetration dominates the stochastic merit-order effect, leading to increased variation in wholesale electricity prices. First, we recast our main specification, except that we keep our data in levels instead of converting it to natural logs (WPV share remains on the 0–100 scale, as does the RPS percentage requirement). Second, still keeping our data in levels, instead of quarterly variances we use quarterly standard deviations for all price and temperature data. Third, we check to see if our main specification results are robust to using both monthly and annual—rather than quarterly—periodicity. Fourth, we disaggregate wind and solar PV to investigate whether the two have different effects on price variance. Last, we use the share of WPV in total generation—rather than capacity—as the key variable of inference. For brevity, some results discussed in this section are reported in our Online Appendix.

22. Despite this, the Stock-Yogo critical value for 10% maximal size bias indicates the IV estimator on WPV share is still asymptotically consistent, and that weak instruments are not a major cause for concern.

5.1 Levels Models

Economists are accustomed to converting data to natural logs as a means of linearizing non-linear structural equations, but there is no *a priori* reason to assume the relationship between WPV share and quarterly wholesale price variance is not (at least approximately) linear. Although our preferred specification assumes it is not, it is still informative as a robustness check to run our main specification with all data in levels instead of logs. Table 5 presents the OLS and IV results of these models.

Overall, results are consistent with those of Table 4, with some exceptions. Our main coefficient of interest remains negative with OLS but is not statistically significant. With IV, we again find that the impact of an increase in WPV share on price variance is positive and significant. With respect to magnitude, the point estimates are quite comparable. Recall that in our main specification, a back-of-the-envelope computation of the estimated increase in wholesale price variance from a one percentage-point increase in WPV share, using our IV estimates, translated to an increase in quarterly standard deviation of wholesale prices ranging between \$0.98 and \$1.18 USD/MWh. When the data are in levels, the estimated increase in standard deviation ranges between \$1.11 and \$1.35 USD/MWh.

Another notable change is that the IV models using the contemporaneous FIT values as instruments (Online Appendix, Tables A5 and A6) perform better in terms of the diagnostic test statistics than do those using the one-year change in FIT values—the opposite of the outcome when the data are in logs. The IV models reported in Table 5 suffer from potential weak instrumentation issues, which is also likely the cause of a failure to reject the null of the under-identification test at 90 percent confidence as well. Ultimately, however, the weak instrument robust inference test confirms that this is not much cause for concern. The levels models provide further support for the identification of the effect of WPV share on wholesale electricity price variance, and that the intermittency effect of these power sources dominates the stochastic merit-order effect.

5.2 Levels Models Using Standard Deviation

In our second set of robustness checks, we maintain our data in levels, but instead use quarterly price standard deviation, $SD_{i,s} \equiv \sqrt{V_{i,s}}$, as the dependent variable. We expect a statistically significant effect of WPV share on price variance to translate to an in-kind effect on standard deviation. Indeed, if this were not the case—or if the magnitudes of the marginal effects were significantly discordant with those for price variance—it would certainly be cause for concern. Note that we keep the data in levels here because the log of variance is precisely two times the log of standard deviation; the result is that coefficient estimates of regressions using the log of standard deviation are a simple linear transformation of the coefficient estimates when the log of variance is used. Among our covariates, we also convert the quarterly variances of natural gas and oil prices and daily maximum and minimum temperatures into quarterly standard deviations as well.

Table 6 presents these results, which are largely consistent with our main specification. With OLS, the estimated effect is negative, but is statistically significant at 90% in Model (1) only. Conversely, the effect is positive and statistically significant at 95% or better in all IV models. The magnitude of the estimated effect ranges between \$0.73 and \$0.92 USD/MWh, which is again comparable to the effect implied by our main specification results. One issue, however, is that we reject the null in the test of over-identifying restrictions. The alternative instrumentation using contemporary FIT values and Kyoto Protocol ratification (Online Appendix, Tables A7 and A8) yields qualitatively similar results, and does not suffer from this issue.

Table 5: OLS and second-stage IV estimates of Eq. (1), data in levels. Dependent variable: $V_{i,s}$.

	(1)	(2)	(3)	(4)	(5)	(6)
WPV share	–21.64	–17.25	–17.70	43.03**	50.04**	52.55**
	(15.05)	(15.85)	(16.31)	(18.60)	(24.03)	(24.59)
Total electricity generation	0.00	0.00	0.00	0.00**	0.00***	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Variance, Henry Hub NG price	0.50	0.51	0.35	1.05***	1.05***	1.03**
	(0.57)	(0.57)	(0.67)	(0.41)	(0.40)	(0.42)
Variance, Brent crude oil price	0.87	0.87	0.85	0.21	0.21	0.24
	(0.62)	(0.62)	(0.59)	(0.26)	(0.26)	(0.27)
GDP		–544.19**	–561.69**		–375.47	–400.48
		(265.15)	(252.46)		(425.92)	(405.16)
Population		97.63*	102.14**		51.29	59.78
		(52.75)	(48.44)		(89.19)	(83.81)
CO_2 emissions from electricity sector		2.26**	2.29**		1.45	1.76
		(1.11)	(1.08)		(1.72)	(1.64)
Variance, maximum daily temperature			22.49*			–14.13
			(13.35)			(9.77)
Variance, minimum daily temperature			–11.41			16.16
			(8.26)			(10.11)
Specification	OLS	OLS	OLS	IV	IV	IV
Observations	520	520	520	446	446	446
R^2	0.23	0.23	0.23	0.15	0.15	0.16
IV diagnostics						
First-stage F-test of excluded instruments (p-value)				0.00	0.00	0.00
Under-identification (Kleibergen-Papp rk LM stat, p-value)				0.10	0.12	0.12
Over-identification (Hansen's J, p-value)				0.28	0.25	0.24
Weak identification (Cragg-Donald Wald F-stat)				22.21	21.12	21.09
Stock-Yogo critical value: 10% max. F-stat size bias				22.30	22.30	22.30
Stock-Yogo critical value: 5% max. bias relative to OLS				13.91	13.91	13.91
Weak instrument robust inference (Andersen-Rubin χ^2, p-value)				0.03	0.05	0.03

NOTES: (i) First-stage estimates for IV specifications in columns (4)-(6) reported in Online Appendix, Table A5, columns (1)-(3), respectively. (ii) All models include country, year, and quarter fixed effects with robust standard errors clustered by country group-year. (iii) * p<0.10, ** p<0.05, *** p<0.01

5.3 Logs Models Using Monthly and Annual Periodicities

Next, we run our main specification again with the exception that the data are observed at either monthly or annual periodicities. Table 7 presents the results using monthly data. The results using annual data are presented in the Online Appendix.

Monthly. Our regression results when all data are observed at a monthly interval are highly consistent with the results of our main specification, with one exception—it is the monthly variance of *oil* prices rather than natural gas prices that appears to have the statistically significant relationship with monthly wholesale electricity price variance. This unexpected reversal notwithstanding, the consistency of our main coefficient of interest with its counterpart in Table 4 is reassuring. As before, the alternative instrumentation specification using contemporaneous FIT values and Kyoto Protocol ratification are presented in the Online Appendix (Tables A9 and A10), and yield very similar results.

Annual. When the data are converted to yearly observations (Online Appendix, Tables A11 and A12), we lose most of our statistical significance simply because the number of observations is too low. Depending on the specification, we have only 113 or 132 annual observations. This causes several problems with the validity of the instrumental variables; our IV diagnostic tests indicate that both the under-identification and weak instrument tests fail. Point estimates for our

Table 6: OLS and second-stage IV estimates of Eq. (1), data in levels. Dependent variable: $SD_{i,s} = \sqrt{V_{i,s}}$ (quarterly standard deviation).

	(1)	(2)	(3)	(4)	(6)	(8)
WPV share	–0.34*	–0.25	–0.27	0.73***	0.89***	0.92***
	(0.18)	(0.19)	(0.20)	(0.25)	(0.32)	(0.33)
Total electricity generation	0.00	0.00	0.00	0.00***	0.00***	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
St. dev., Henry Hub NG price	0.40**	0.41**	0.37*	0.55***	0.55***	0.53***
	(0.20)	(0.20)	(0.19)	(0.18)	(0.18)	(0.17)
St. dev., Brent crude oil price	0.34	0.34	0.33	0.08	0.09	0.09
	(0.24)	(0.24)	(0.23)	(0.17)	(0.17)	(0.17)
GDP		–10.11**	–10.18***		–6.24	–6.45
		(3.89)	(3.74)		(6.36)	(6.19)
Population		1.86**	1.89**		0.89	0.97
		(0.79)	(0.75)		(1.34)	(1.30)
CO_2 emissions from electricity sector		0.05***	0.05***		0.04	0.04
		(0.02)	(0.02)		(0.03)	(0.03)
St. dev., maximum daily temperature			3.10*			–1.73
			(1.59)			(1.16)
St. dev., minimum daily temperature			–1.65			2.78**
			(1.11)			(1.36)
Specification	OLS	OLS	OLS	IV-1	IV-2	IV-3
Observations	520	520	520	446	446	446
R^2	0.33	0.34	0.35	0.34	0.34	0.35
IV diagnostics						
First-stage F-test of excluded instruments (p-value)				0.00	0.00	0.00
Under-identification (Kleibergen-Papp rk LM stat, p-value)				0.10	0.12	0.11
Over-identification (Hansen's J, p-value)				0.08	0.08	0.06
Weak identification (Cragg-Donald Wald F-stat)				22.25	21.16	21.17
Stock-Yogo critical value: 10% max. F-stat size bias				22.30	22.30	22.30
Stock-Yogo critical value: 5% max. bias relative to OLS				13.91	16.85	13.91
Weak instrument robust inference (Andersen-Rubin χ^2, p-value)				0.00	0.01	0.00

NOTES: (i) First-stage estimates for IV specifications in columns (4)-(6) reported in Online Appendix, Table A7, columns (1)-(3), respectively. (ii) All models include country, year, and quarter fixed effects with robust standard errors clustered by country group-year. (iii) * p<0.10, ** p<0.05, *** p<0.01

other covariates also swing wildly from model to model, which is problematic. It is worth noting, however, that despite a lack of statistical significance at acceptable levels of confidence (p-values range between 0.2 and 0.4), the signs of the coefficient estimates on WPV share follow a similar pattern to that observed in Table 4—they are negative when OLS is used, but positive when IV is used. We find it likely that if we had the requisite data to provide a greater number of annual observations, statistical significance would emerge in these regressions as well.

5.4 Other Robustness Checks

As noted earlier, wind and solar PV, although both intermittent technologies, have different temporal variation patterns that affect sub-daily load profiles in different ways. The implication is that measuring the effect of the combined WPV share on daily wholesale price variation does not capture any differences in price dynamics related to the differences in sub-daily intermittent fluctuations. To test whether such differences are statistically significant in terms of their effects on quarterly price variance, we recast our IV specification with separate wind-share and PV-share first-stage regressions. We then run a simple test to see if the difference in the separate second-stage coefficient estimates of the effects of these shares on price variance is statistically different from

Table 7: OLS and second-stage IV estimates of Eq. (1), monthly data. Dependent variable: ln($V_{i,m}$) (monthly standard deviation).

	(1)	(2)	(3)	(4)	(6)	(8)
WPV share	–0.05**	–0.05**	–0.05**	0.08***	0.09**	0.09**
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)
Ln(Total electricity generation)	1.47***	1.44***	1.30**	1.12**	1.13**	0.95*
	(0.51)	(0.52)	(0.52)	(0.54)	(0.56)	(0.56)
Ln(Variance, Henry Hub NG price)	0.03	0.03	0.03	0.06	0.06	0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Ln(Variance, Brent crude oil price)	0.17***	0.17***	0.16***	0.19***	0.19***	0.19***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Ln(GDP)		–0.15	–0.10		0.37	0.49
		(1.01)	(0.98)		(1.23)	(1.23)
Ln(Population)		2.22	1.55		–6.24	–7.28
		(6.36)	(6.40)		(9.73)	(10.07)
Ln(CO_2 emissions from electricity sector)		0.22	0.23		0.54	0.56
		(0.92)	(0.92)		(1.04)	(0.93)
Ln(Variance, maximum daily temperature)			0.12			–0.04
			(0.10)			(0.12)
Ln(Variance, minimum daily temperature)			–0.02			0.13
			(0.09)			(0.11)
Specification	OLS	OLS	OLS	IV	IV	IV
Observations	1552	1552	1552	1332	1332	1332
R^2	0.63	0.63	0.63	0.60	0.60	0.60
IV diagnostics						
First-stage F-test of excluded instruments (p-value)				0.00	0.00	0.00
Under-identification (Kleibergen-Papp rk LM stat, p-value)				0.09	0.08	0.08
Over-identification (Hansen's J, p-value)				0.77	0.76	0.80
Weak identification (Cragg-Donald Wald F-stat)				97.38	79.70	79.76
Stock-Yogo critical value: 10% max. F-stat size bias				22.30	22.30	22.30
Stock-Yogo critical value: 5% max. bias relative to OLS				13.91	13.91	13.91
Weak instrument robust inference (Andersen-Rubin χ^2, p-value)				0.05	0.09	0.09

NOTES: (i) First-stage estimates for IV specifications in columns (4)-(6) reported in Online Appendix, Table A9, columns (1)-(3), respectively. (ii) All models include country, year, and month fixed effects with robust standard errors clustered by country group-year. (iii) * p<0.10, ** p<0.05, *** p<0.01

zero. If so, this would imply that differences in the sub-daily dynamics of wind versus solar PV may require different approaches—e.g., in terms of price risk mitigation strategies—depending on the relative shares of either technology in the overall generation mix. Results of this specification are presented in the Online Appendix (Tables A13 and A14), and the second-stage results also contain the coefficient comparison test statistics. Overall, results are generally consistent with those of our main specification—coefficient estimates on both wind and solar shares are positive and of comparable magnitude—but we lose a great deal of statistical significance on the separate effects, particularly for solar, as compared to combined WPV share. This is not surprising, given that solar accounts such a small share of the overall generation mix.[23] More importantly, the point estimates for each effect are quite comparable; the difference between them is not statistically different from zero. This provides reassurance that using combined WPV shares is not distorting our main results in an economically meaningful way.

23. This is also the likely explanation for the negative significant coefficients on the RPS percentage requirement and the wind FIT in the first stage PV-share regressions. RPS directs investment toward the lowest cost alternative; wind is cheaper, so an incremental increase in the RPS percentage requirement provides more incentive to invest in wind capacity and than in PV capacity. A greater wind FIT induces investment in wind capacity but would not affect investment in PV capacity. In either case, given a sufficient increase in total generation, the share of PV would decline.

Finally, we have used the share of WPV in total capacity as the primary variable of inference throughout this analysis. This choice is based on data availability. We simply do not have reliable data on wind or solar PV generation at a sufficiently disaggregated level to measure accurate quarterly WPV generation shares for all countries in our sample. The drawback is that differences in capacity factors across countries due to variation in the favorability of weather and climate conditions would imply differences in WPV output per unit capacity. Using variation in WPV generation shares across countries may yield different results than using variation in the share of WPV in total capacity. To test this using available data, we impute quarterly WPV generation at the country level using the EIA's annual data on WPV generation and long-run historical averages of seasonal wind speeds and solar insolation. This method naturally implies substantial measurement error. In our Online Appendix (Tables A15 and A16) we report the results of IV models using this noisy measure of quarterly WPV generation shares in place of WPV capacity shares. Results are largely consistent with those of our main IV specification. The estimate for the effect of WPV generation share on price variance is quite similar to its counterpart in Table 3, although it is not quite statistically significant at 90% confidence—likely a result of the unavoidable measurement error.[24] This does, however, provide reassurance that our results are not driven by our use of WPV capacity shares instead of WPV generation shares.

6. CONCLUSION

The goal of this research has been to examine the effect that greater penetration of intermittent energy sources—specifically wind and solar PV (WPV)—is likely to have on the variation in wholesale electricity prices. We offered simple theoretical demonstrations of why greater WPV penetration might either reduce or increase electricity price variation. On one hand, WPV enters at the base of the merit order, shifting the total electricity supply curve outward such that a stochastically fluctuating demand curve intersects it at a flatter portion. This would lead to a tighter distribution of equilibrium wholesale prices, which we refer to as the *stochastic merit-order effect*. Conversely, the intermittency of WPV also likely results in stochastic shifts of the total electricity supply curve, leading to greater price variance. We envision these two countervailing effects as occurring simultaneously.

Using an unbalanced panel dataset of 19 countries over the period 2000–2011 we empirically tested whether one or the other dominates. Specifically, we regressed the (log) quarterly variance in electricity prices on the share of WPV in total generation capacity, controlling for other relevant factors. We utilized an instrumental variables (IV) specification, due to the likelihood that a country's WPV share is endogenous to price variability—greater price variance presents a disincentive to invest in WPV, implying biased OLS estimates.

Our IV estimates indicate a robust, statistically significant, positive relationship between WPV penetration and wholesale electricity price variance. In other words, the intermittency effect dominates the stochastic merit-order effect. This suggests a mostly overlooked consequence of greater WPV penetration: wholesale electricity prices are more volatile in the short run the greater is WPV penetration, thus increasing price risk in competitive wholesale electricity markets. This

24. Here also, the coefficient on the RPS percentage requirement in the first-stage regressions is negative. This is because biomass generation is eligible under most RPS schemes; in many countries a larger proportion of the RPS requirement is met by biomass than by WPV. Thus, a marginal increase in the RPS requirement leads to a smaller increase in WPV generation than in biomass generation. If total generation increases by more than the induced increase in WPV generation, the share of WPV would decline.

implies electric utility providers must devote more resources to risk management strategies such as hedging and futures trading. The costs of such activity, and of the pure risk itself, must ultimately be borne by electricity consumers by way of higher risk premiums embedded in retail power rates.

Our results also suggest an important question for future research—whether the increase in wholesale electricity price variation associated with greater WPV penetration would lead to worsened forecasting accuracy. Price forecasts comprise a fundamental aspect of risk management in electricity markets. Researchers and industrial analysts have continuously sought to improve forecasting techniques for electricity prices.[25] Our results suggest that because WPV penetration is associated with increased wholesale price variability in the short run, this increase in price instability is likely associated with wider forecast errors. On the other hand, as grid operators improve their ability to forecast WPV generation over time, they may become more efficient in forecasting the resulting price fluctuations. Grid operators may become more proactive than reactive in ramping conventional power generation up or down in response to forecast WPV fluctuations, thereby mitigating price variation. More research is needed to investigate the effects of the stochastic merit-order and intermittency effects on electricity price forecast accuracy.

An important caveat to our study is that we have focused exclusively on the *short-run* variance in electricity prices—measured at a quarterly interval—which we feel is a relevant metric by which to measure risk in electricity markets. At any rate, it is the one we are best able to measure given the available data. It is difficult to know the extent to which short-run variance (and, therefore, risk) translates to long-run variance. Any number of long-run factors that cannot be incorporated into our model cloud our inferential capabilities about long-run variability. More research is needed to study long-run behavior; we do not yet have detailed enough data for enough countries over a long enough time span to test the hypothesis credibly in a long-run setting.

In closing, we believe our results have relevance beyond just wind and solar penetration. A similar intuition holds for any intermittent source of electricity generation that has zero (or near-zero) marginal cost. The resulting stochastic merit-order and intermittency effects should impact wholesale price variation just the same. As countries around the world seek to increase the shares of various forms of renewable power generation in their overall energy portfolios, it will be of interest to ascertain whether wholesale price variation increases as a result. Our study suggests it will. Such a shift would thus carry latent costs from increased price risk in competitive wholesale electricity markets. A subtler implication is that commercial-scale electricity storage may ultimately be more important than previously thought for wind and solar PV to be harnessed to their full potential. Without storage to ameliorate supply intermittency (and absent costly market interventions designed to boost penetration) the increased price risk resulting from wind and solar PV may ultimately lead to under-investment relative to what would be required to reduce CO_2 emissions to sustainable levels.

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25. For example, given the high seasonal and intraday cyclicality of electricity demand, a number of studies have identified the ARCH-GARCH family of models (Engel 1982; Bollerslev 1986) as the most appropriate forecasting tool for electricity prices (e.g., Hadsell et al. 2004; Garcia et al. 2005; Worthington et al. 2005).

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ONLINE APPENDIX URL:

https://www.dropbox.com/s/ffgnrjavtxnewa3/Johnson_Oliver_Online_Appendix.pdf?dl=0.

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