Electricity Expenditure Risk with Renewable Energy Support Schemes[†]

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Abstract:
In deregulated electricity markets, economic support schemes for renewable energy (RES-E) technologies are typically implemented under the pretense of shielding investors from revenue risk arising from stochastic wholesale electricity prices. Two dominant RES-E support policies worldwide are feed-in tariffs (FIT) and renewable portfolio standards (RPS). Thus far, the economic and policy literature has failed to acknowledge a key benefit to retail electricity providers (and, ultimately, to consumers)—that stimulating investment in RES-E generation itself reduces wholesale price risk. Using a simple theoretical model of an electricity market, we demonstrate that greater RES-E generation should reduce the short-run variance in the wholesale electricity price, and thus in total electricity expenditures per unit (which include payments to RES-E related to the prevailing support policy). We find empirical support for this hypothesis using a panel of policy, price, and generation data for 19 countries over the period 2000-2011. Both FIT and RPS are found to reduce the short-run variance in total electricity expenditures per unit, due largely to a reduction in the variance in wholesale prices. Moreover, we find evidence that FIT reduces the variance in electricity expenditures per unit over the long-run, whereas RPS does not.

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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. In the electricity sector, most renewable technologies are not yet competitive with conventional fossil fuels due to higher generation costs per kilowatt-hour (kWh). This disadvantage inhibits incentives for investment in renewable generation capacity. Many governments around the world have implemented economic support policies to stimulate investment in renewable generation, with the ultimate goal of reducing carbon emissions in response to increased public concern over the potential risks of anthropogenic climate change. Two dominant renewable support policies have emerged. Feed-in tariffs (FIT) guarantee that all eligible renewable-energy-source electricity (RES-E) producers receive a fixed price (or fixed premium) per kWh generated, and obligate the nearest utility provider to purchase and distribute all available RES-E (Cory *et al*. 2009; Mendonça *et al*. 2010). By contrast, under a renewable portfolio standard (RPS), retail electricity providers are required to procure a specific proportion of supply from renewable sources.

A robust literature spanning disciplines such as economics, policy, and electrical systems engineering has sought to compare and contrast RPS and FIT on multiple dimensions (see Section 2 for a thorough review). We contribute to this literature by exploring a previously overlooked aspect of the RPS-FIT comparison. Specifically, our goal is to empirically examine the short- and long-run variance – that is, risk – faced by retail utility providers with respect to per-unit electricity expenditures that emerges under RPS and FIT schemes. It is well known that deregulated electricity markets are prone to significant variability in wholesale prices, resulting from a number of factors including (but not limited to) variation in fuel prices, availability of generation capacity, unexpected outages, demand elasticity and exogenous demand variations, the lack of large-scale storage capability, and transmission constraints (Benini *et al.* 2002). Stochastic price fluctuations, compounded by the ‘intermittency’ problem associated with key renewable technologies like wind and solar, imply risk and uncertainty are unavoidable aspects of the renewable generation problem.

Proponents of FIT argue that it insulates investors from revenue risks associated with electricity price variability. But investors are not the only market participants to whom a reduction in this specific source of risk might be considered beneficial. Retail electricity providers mitigate wholesale price risk through hedging, futures markets, and other potentially costly risk management strategies, but are unable to perfectly shield themselves from price risk. Thus, the costs of such risk faced by electrical utilities must ultimately be borne in the form of higher risk premiums passed on to electricity consumers.

Intuitively, in the short run *any* policy that stimulates RES-E generation should reduce the variability electricity expenditures per unit paid by utilities. As we explain below using a simple appeal to theory, this is because an increase in RES-E generation shifts the conventional electricity supply curve outward, implying the stochastically fluctuating demand curve intersects it at a flatter section, thus suppressing the resulting price variability (Johnson and Oliver 2016). We find empirical support for this theory by regressing the quarterly variance of total electricity expenditures per unit on FIT and RPS indicators, controlling for a number of other relevant covariates. We find that both FIT and RPS reduce the variance in total electricity expenditures per unit. As a secondary hypothesis, we test whether FIT reduces total electricity expenditures by more than RPS due to the fixed price design. We find this to be the case qualitatively, despite being unable to reject the null hypothesis of no statistically significant difference between the estimated coefficients. The intuitive conclusion is that the reduction in variance is driven primarily by the supply-curve effect. The implication is that from the standpoint of retail electricity providers, either policy is effective at reducing short-run wholesale price risk.

Perhaps the most closely related paper to our short-run analysis comes from the operations research literature. Wozabal *et al*. (2014) develop a similar theoretical model to examine the effect of intermittent energy sources on electricity price variance. Much like our use of quarterly variance in electricity expenditures per unit (essentially a weighted average price) as the dependent variable in our regressions, Wozabal *et al*. use intraday price variance (in the German power market only). The distinction is thus short run versus *very* short run. Wozabal *et al*. find that increased production of intermittent generation generally reduces wholesale price variance in the very short run, although the opposite occurs for "very low and very high" levels of intermittent generation relative to total demand. Ultimately the effects depend on the distribution of intermittent generation and the slope of the supply function, which complements own model predictions and empirical findings.

We also examine how the presence of RES-E support policies affects the long-run variance in electricity expenditures per unit. Our long-run model and empirical specification are motivated by Schmalensee's (2012) theoretical model of long-run electricity expenditure variance under FIT and RPS. Using cross-country variation in trends in electricity expenditure variance, we find evidence that FIT reduces long-run variance in electricity expenditures —and therefore long-run expenditure risk. For RPS we are unable to reject the null hypothesis of no effect on long-run electricity expenditure risk. As we explain, these results run counter to Schmalensee's prediction.

The remainder of the paper proceeds as follows. Section 2 provides a detailed overview of RPS and FIT with a review of the existing literature on the advantages and disadvantages of each policy. In section 3, we describe the simple theoretical intuition for why the variance in short-run electricity expenditures per unit should be expected to fall as a result of RES-E support policies. Section 4 describes our data, empirical design, and estimation results, and provides further discussion of the implications for policy and industry. Section 5 reviews Schmalensee's (2012) theoretical model and provides a limited test of the effects of RES-E support schemes on long-run electricity expenditure risk. Section 6 concludes. We also provide an appendix with more detailed information on our data.

2. Policy Overview: FIT versus RPS

2.1. Feed-in Tariffs

FIT supports investment in RES-E in two ways.[1] First, it guarantees that all eligible producers receive per kilowatt-hour (KWh) a fixed price or the spot price plus a fixed premium (Cory *et al*. 2009). Second, the nearest utility provider is obligated to purchase and distribute all RES-E that 'feeds-in' to the grid, regardless of electricity demand

[1] For a complete overview, see Mendonça *et al*. (2010). A more concise, but sufficiently informative review of alternative FIT design options is available in Couture and Gagnon (2010).

(Mendonça *et al*. 2010). Successful FIT design typically determines tariff levels based on a generator's 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 generation), inflation and interest, and a rate of return on investment (Klein *et al*. 2010). Generally, cost amortization requires that a shorter period of guaranteed payment be associated with a higher tariff. Worldwide, the most commonly used remuneration period is 15-20 years, where 20 years is considered to be the average life of a typical renewable energy plant (Mendonça *et al*. 2010). Finally, most FITs provide for (i) 'tariff digression'; and (ii) tariff review and revision. Tariff digression is defined as a level of remuneration that 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. The possibility of review and revision reflects an acknowledgment of underlying technological and market developments that may unexpectedly affect capacity costs due to input price shocks (Klein *et al*. 2010).

2.2. Renewable Portfolio Standards

RPS is a quantity-based instrument in which the regulator requires that a specific proportion of electricity come from renewable sources (typically per year). Electric utilities can meet RPS requirements by purchasing RES-E from independent generators, or through the installation and operation of their own facilities (Wiser *et al*. 2005). Successful implementation of RPS policy typically includes a complementary market for tradable renewable energy certificates (RECs).[2] For every megawatt-hour (MWh) of RES-E generated, a REC is created. The utility pays the renewable generator for both the electricity supplied and the REC, providing renewable generators with a supplemental income stream. Each year, RECs are surrendered to the jurisdictional regulator to demonstrate compliance with the RPS. Alternatively, RECs can usually be 'banked' for future use (Johnson 2014). Utilities with RECs in excess of the RPS requirement can sell

[2] Also commonly referred to as 'tradable green certificates'.

them in the market for RECs, while others might purchase RECs as a substitute for purchasing electricity directly from renewable generators (Wiser and Barbose 2008).[3]

2.3. Advantages and Limitations of FIT and RPS

A number of studies have explored the advantages and disadvantages of FIT and RPS schemes based on various objective criteria.[4]. While an exhaustive review is not possible here, we review what we believe to be the main findings of the existing literature.

There are many risks involved in the development of RES-E generation capacity. Dinica (2006) provides a complete discussion of FIT and RPS from the viewpoint of investors with regard to the various sources of risk. FIT design itself imposes policy risks on investors including uncertainty over the duration of the administrative process or unexpected changes in the remuneration level.[5] At the core of the investment decision, however, are electricity price risk and the reliability of purchase contracts. A fixed price FIT with a purchase obligation insulates investors from risks associated with electricity price variability and contract uncertainty, while eliminating windfall profits associated with exceptionally high spot prices.[6] Guaranteed payments provide renewable generators with unmatched security regarding future revenues, and investors are remunerated based on the actual costs of renewable energy project development. This characteristic is especially attractive for the financing of capital-intensive technologies with high entry costs and a high ratio of fixed to variable costs (Couture and Gagnon 2010).

FIT policy has its drawbacks. In isolation, state or national remuneration levels may produce the desired effect of supporting the local diffusion of RES-E. With fully open borders, however, FIT may be undermined as supported renewable sources compete

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[3] See Amundsen and Mortensen (2001) for formal analytical treatment of the quota system (RPS) with tradable green certificates (RECs).

[4] Many have compared and contrasted FIT and RPS with other RES-E support schemes, including investment tax credits, production subsidies, clean energy standards, net metering, carbon emissions taxes, carbon cap-and-trade, bidding auctions for long-term purchase contracts, and others (*e.g*., Madlener and Stagl, 2005; Palmer and Burtraw, 2005; Huber *et al*. 2007; Finon and Perez 2007; Mulder 2008; Timilsina *et al*. 2012; Fell and Linn 2013; Johnson 2014). Some researchers have also begun to study the implications of overlapping RES-E support policies (*e.g.* Cory *et al*. 2009; Fischer and Preonas 2010; Böhringer and Rosendahl 2010).

[5] Lüthi and Wüstenhagen (2012), for example, find experimental evidence that solar PV developers, in deciding between investment opportunities in different countries, weigh FIT-based returns against various policy risks, ultimately choosing the country with the most favorable risk-return profile.

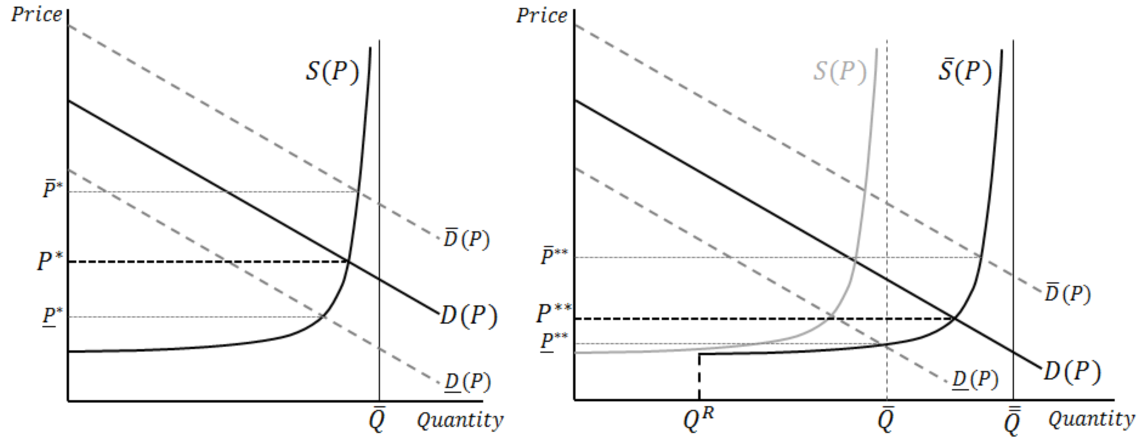
[6] With a fixed premium FIT, investors are exposed to price risk but guaranteed a minimum payment per kWh, with the opportunity to collect windfall profits when spot prices spike (Gross *et al*. 2010).

with each other. For example, in the absence of a single, harmonized FIT for the entire European market, Ringel (2006) points out that FIT may create a competitive advantage for (1) technologies with high support levels; (2) countries with large natural endowments of renewable generation potential; or (3) countries with unambitious targets for the penetration of renewables. As a result, either a race-to-the-bottom on environmental stringency or a race-to-the-top on remuneration levels may ensue. A more common critique of FIT is that it may fail to provide incentive for cost-reducing technological improvements (Mitchell 2000; Menteneau *et al*. 2003; Söderholm and Klaasen 2007; Butler and Neuhoff 2008; Tamás *et al*. 2010). Because renewable developers do not face price competition, FIT sacrifices least-cost efficiency in exchange for greater and more rapid diffusion. Popp *et al*. (2011), however, find no statistically significant effect of FIT or RPS on technological advancements in the renewable energy sector.

RPS exhibits an entirely different set of advantages and limitations. Because RPS ensures that renewables attain a specific market share, the regulator is able to directly calculate the program's contribution toward the environmental goal of CO_2 reduction (Berry and Jaccard 2001). Moreover, by requiring retail electricity providers to procure a mandated minimum proportion of their supply via renewable sources at market prices, RPS obligations encourage renewable generators to meet the target in a least-cost fashion (Wiser and Barbose 2008). In theory, this cost competition among renewable developers incentivizes economic efficiency through technological improvement, and the cost reductions can then be passed on to consumers.

Some researchers have concluded that RPS exhibits *static efficiency,* yet suffers in terms of *dynamic efficiency* (*e.g*. Finon and Menteneau, 2004; Finon, 2006; Finon and Perez, 2007). That is, RPS efficiently allocates the quota obligation across renewable producers in the short-run, which occurs where marginal production costs are equalized across producers. However, precisely because RPS favors the least-cost renewable generators in the short run, this creates a disincentive for the development of less mature, higher cost technologies over the long run. Thus, RPS fails to provide fertile ground for the development of a wide range of renewable technologies.[7] Johnstone *et al*. (2010) find empirical evidence that RPS is more likely to induce innovation in renewable generation

[7] See Buckman (2011) for variants on the RPS framework designed to correct for this weakness.



(a) Without RES-E support **(b)** With RES-E support

Figure 1. Simple model of an electricity market. Source: Johnson and Oliver (2016)

technologies (like wind power) that are "close to competitive with" conventional fossil power, but not for higher-cost technologies (like solar PV). Finally, because consumers ultimately bear the cost of a renewable policy's influence over the energy supply mix, retail electricity price effects are an important indicator of the welfare burden. Fischer (2010) shows that when the supply curves of non-renewable generation are not perfectly flat, consumer electricity prices fall under RPS only when the quota is low. When the quota is high, however, electricity prices rise steeply. Palmer and Burtraw (2005) find a similar result.

3. A Simple Model of Short-run Electricity Expenditure Risk

To provide our own intermediate-level microeconomic intuition for why RES-E support policies might be expected to reduce short-run electricity expenditure risk, we recap the theory proposed in Johnson and Oliver (2016). Consider the simple diagrammatic model presented in Figure 1. Let $D(P)$ be the inverse electricity demand curve, where P is the wholesale price of electricity. Assume $D(P)$ has some stochastic component (related to weather, for example) that causes it to shift up and down in the short-run. For simplicity, define $\overline{D}(P)$ as the upper limit for a positive short-run demand shock and $\underline{D}(P)$ as the lower limit for a negative demand shock. Let Q denote the quantity demanded/supplied.

Assume the short-run supply curve for conventional electricity, $S(P)$, is relatively flat for low supply quantities, 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 RES-E support policy, which we assume results in zero RES-E generation. Given the upper and lower bounds of the stochastic demand curve, the equilibrium wholesale price fluctuates between $\bar{P}^*$ and $\underline{P}^*$. In panel (b), the RES-E support policy induces RES-E generation amount Q^R, shifting the entire supply curve to the right, from $S(P)$ to $\bar{S}(P)$, and effectively increasing maximum generating capacity from $\bar{Q}$ to $\bar{\bar{Q}} = Q^R + \bar{Q}$. With RES-E generation, the equilibrium wholesale price of electricity falls from P^* to P^{**}, consistent with the analysis of Sáenz de Meira *et al*. (2008). Additionally, it is easy to see that the range of variation in the wholesale price is lower, fluctuating between $\bar{P}^{**}$ and $\underline{P}^{**}$. Thus, we should expect that *any* policy leading to a short-run increase in RES-E generation should result in lower variability in the wholesale price – and therefore in total electricity market expenditures per unit – driven by movement downward along the conventional electricity supply curve.[8] Note that the same argument holds even if Q^R is stochastic because of intermittency. Hereafter, we refer to this as the 'supply curve effect.'[9]

In addition to this electricity supply effect, we expect that FIT should reduce the variation in electricity expenditures per unit by more than RPS, simply because of the fixed-price design. We will refer to this as the 'fixed-price effect' of FIT. Intuitively, we expect the fixed-price effect to be small, simply because even countries with relatively extensive RES-E generation capacity, the proportion of FIT-eligible producers in the overall energy mix will be small. We now turn to an empirical test of these hypotheses using international data on wholesale electricity prices and generation.

[8] Note also that our simple model predicts a general reduction in wholesale electricity prices, consistent with the finding of Sáenz de Meira *et al*. (2008).

[9] It is not necessarily true that total electricity expenditures will decrease since under either support policy, there are additional payments to renewable generators that may, in theory, increase total expenditures if the premiums are sufficiently high.

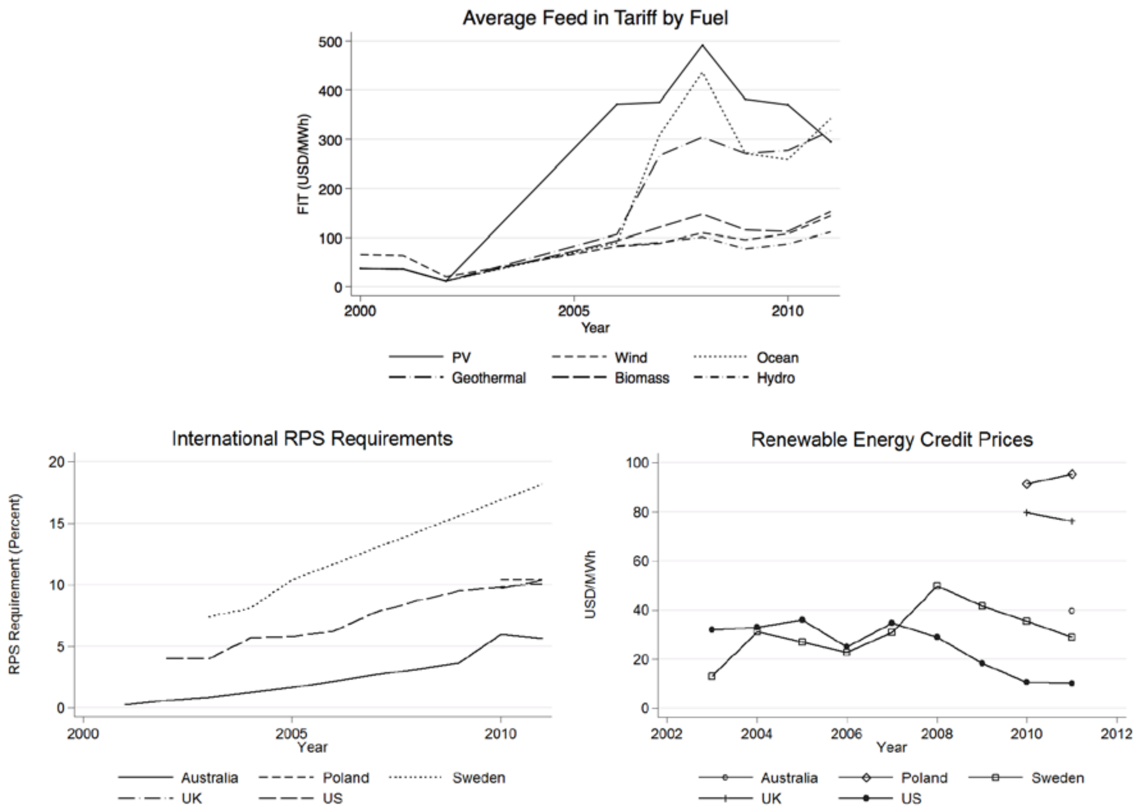


Figure 2. Sample FIT, RPS, and REC data.

4. Empirical Analysis

4.1. Description of the Data

The final sample used in our estimation consists of an unbalanced panel of 19 countries over the period 2000-2011. Our data were compiled from multiple sources, rendering the data-cleaning process a formidable one. The reward is that our dataset is entirely unique to this paper.

FIT and RPS data are taken from Johnstone *et al*. (2010), and contain FIT payments (by resource) and RPS requirements for each country at an annual interval. US REC prices[10] were purchased from Marex Spectron; all others are publicly available on the web. Figure 2 displays average FIT payments by resource by year across countries, RPS requirements by country by year, and REC prices by country by year.

[10] These prices are calculated as a weighted average of individual state REC prices, weighted by the RPS requirement in each state. States that do not have REC markets are excluded from this calculation.

Table 1. Summary statistics – daily-level data.

Variable	Mean	Std. Dev.	Min.	Max.
Wholesale price (USD/MWh)	53.50	32.00	-0.72	1,030.72
Expenditure per unit (USD/MWh)	56.74	33.14	0	1,029.88
Total generation (MWh)	1,328,664.18	2,935,004.03	6,886.96	17,633,070
Generation by fuel (*MWh*)				
Fossil, nuclear, & hydro	1,266,497.55	2,846,794.70	180.97	17,343,006
Wind	24,932.26	50,092.91	32.78	386,913.03
Solar PV	1,984.95	7,440.39	0	94,892.77
Solar thermal	208.01	784.36	0	8,639.32
Biomass	30,844.12	48,944.73	772.60	194,039.53
Geothermal	4,128.07	11,044.62	0	41,961.65
Ocean/tidal	69.21	287.96	0	1,421.92

Total number of daily observations: 46,851.

Daily and hourly wholesale electricity prices were in some cases publicly available (*e.g.*, US, Canada, Australia, and New Zealand), but most were purchased from Platts McGraw-Hill (EU and UK) or NordPool Spot (Scandinavian countries). We use spot market prices where available. Where spot prices were not available, we use day-ahead prices.[11] All prices (including FITs and RECs) are converted to constant 2010 US dollars using monthly market exchange rates and annual GDP deflators for each country.[12] Daily total electricity generation data were in most cases publicly available, with the exception of the Scandinavian countries (purchased from Nordpool spot). Table 1 presents summary statistics for the daily price and generation data. A detailed guide to our data sources is provided in the appendix.

To our knowledge, data do not exist for daily electricity generation by fuel across countries. Our only recourse was to construct it – based on several critical assumptions – from daily total generation and monthly- and annual-level generation-by-fuel data:

- *Wind and solar*. We impute monthly wind and solar generation for each country based on International Energy Agency (IEA) annual generation data in conjunction with monthly wind speed and solar radiation data from NASA's Atmospheric Science

[11] For many countries, separate peak and off-peak prices were available. In such cases we create a daily average price, weighted by the fraction of hours in the peak- and off-peak periods. For countries whose wholesale price and/or quantity data were recorded at sub-daily intervals, we computed a quantity-weighted average price for the day.

[12] 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.

Data Center. Daily wind and solar generation is then found by dividing imputed monthly generation by the number of days in the month.

- *Biomass, geothermal, and ocean*. Daily biomass, geothermal, and ocean generation is calculated as a simple daily average based on IEA annual generation data, by dividing annual generation by the number of days in the year.
- *Fossil fuels, nuclear, and hydro*. Subtracting the sum of the above daily generation values for wind, solar, biomass, geothermal, and ocean from total daily generation yields a measure of daily residual generation that must be met by conventional fuels. It does not matter what proportion of daily residual demand is met by nuclear, hydro, coal, oil, or natural gas, since all generation from these sources is paid the same wholesale market price of electricity.[13] On average, in our sample these fuels make up roughly 95 percent of total generation under our assumptions, which is realistic.[14]

Clearly, these constructed data are less-than-ideal. Even so, our assumptions are, to us, the most natural given the constraints of the monthly- and annual-level data that were available. An obvious issue, however, is whether our choices in constructing these data are somehow driving our empirical results. To alleviate this concern, in Section 4.5 we estimate a model that is identical to our main model in every way except that our imputed daily generation values play no role in the estimation. The results are entirely consistent with those estimated from the main model, in which the daily generation data are used.

4.2. Measuring Short-Run Electricity Expenditure Risk

When describing a stochastic economic outcome like total electricity expenditures per unit, variance is, in every practical sense, synonymous with risk. As such, our dependent variable is (log) quarterly variance in electricity expenditures per unit at the country level. We first construct daily electricity expenditure per unit, denoted $\hat{P}_{i,t}$ where i and t index country and day, as a weighted average electricity price. For countries with FIT at date t,

$$\hat{P}_{i,t} = \frac{\sum_j T_{ij,t} Q_{ij,t} + P_{i,t} \sum_k Q_{ik,t}}{Q_{i,t}^{total}}, \tag{1a}$$

[13] Some countries do have FITs for small-scale hydro. We do not have data on small hydro, but assume the proportion of small hydro in total hydro generation to be negligible.
[14] As a point of reference, in 2009 the U.S. generated approximately 4 percent of its electricity from non-hydro RES-E (EIA 2010).

where $T_{ij,t}$ is the FIT paid per unit to eligible source j, $Q_{ij,t}$ is generation by source j, $P_{i,t}$ is the wholesale electricity price, $Q_{ik,t}$ is generation by ineligible source k, and $Q_{i,t}^{total} \equiv \sum_j Q_{ij,t} + \sum_k Q_{ik,t}$. For countries with RPS at date t,

$$\hat{P}_{i,t} = \frac{(P_{i,t} + R_{i,t}) \sum_j Q_{ij,t} + P_{i,t} \sum_k Q_{ik,t}}{Q_{i,t}^{total}}, \tag{1b}$$

where $R_{i,t}$ is the REC price. For countries with neither FIT nor RPS,

$$\hat{P}_{i,t} = \frac{P_{i,t} \sum_k Q_{ik,t}}{Q_{i,t}^{total}}. \tag{1c}$$

For the small fraction of our sample in which a country has both FIT and RPS schemes at the same time, we are unable to observe which eligible producers elect to receive the FIT versus those who participate in the RPS/REC program. Our working assumption is that all eligible production in a given year is allocated to the policy option that results in the highest average payment per unit.

Once $\hat{P}_{i,t}$ was calculated for each country and day in our sample, we then computed $V_{i,s} \equiv \log\left(var[\hat{P}_{i,t\epsilon s}]\right)$, where s indexes quarter. Figure 2 displays $V_{i,s}$ for each country in our sample, and indicates over which interval of the sample the country had either a FIT or RPS scheme in place. Our key variables of inference are dummy indicators for whether a country had a FIT (for at least one fuel) or RPS requirement in a given quarter. Table 2 presents summary statistics for our dependent variable and quarterly control variables (explained below), as well as the fraction of observations (by country-quarter) for which FIT and RPS schemes were in place. Within our sample, FIT is clearly the dominant RES-E support policy, with 54 percent of country-quarters having an active FIT, in contrast to only 19 percent of country-quarters with an RPS. Moreover, it is clear that FIT payments are substantially different across different renewable fuels, reflecting their differing costs. The average FIT payment for wind, one of the cheaper renewable fuels, is \$0.05/KWh, whereas the average FIT payment for solar PV, one of the most expensive renewable fuels, is \$0.17/KWh.

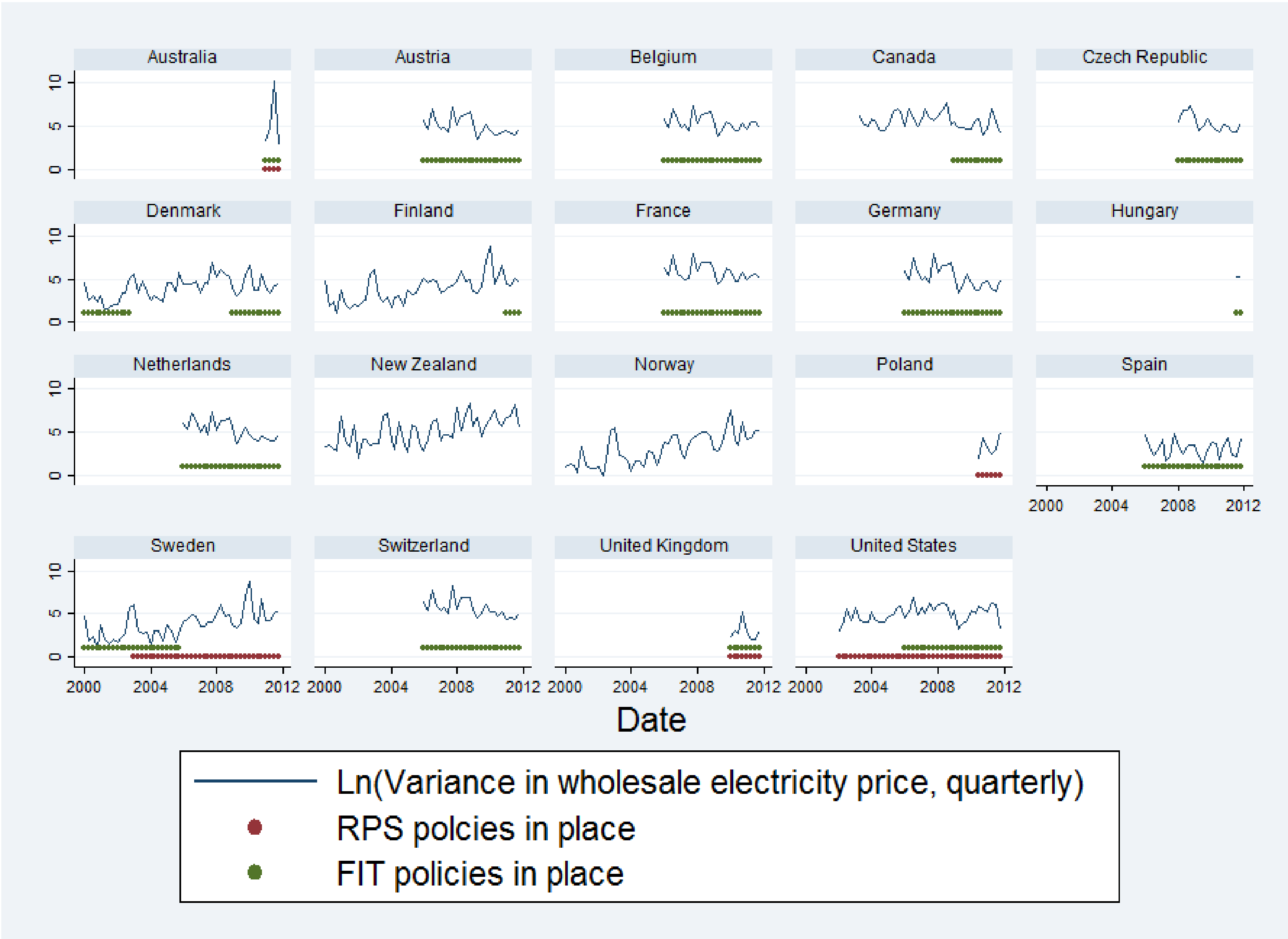


Figure 2. Log of quarterly variance in electricity expenditure per unit by country.

Table 2. Summary statistics – quarterly-level data.

Variable	Mean	Std. Dev.	Min.	Max.
Variance, wholesale price	357.87	1,269.32	1.10	25,424.79
Log(variance, wholesale price)	4.68	1.58	0.09	10.14
Variance, expenditure per MWh	336.70	1,254.12	1.10	25,218.82
Log(variance, expenditure per MWh)	4.56	1.59	0.09	10.14
FIT (any fuel)	0.55	0.50	0	1
RPS	0.18	0.39	0	1
Log(variance, cost per MWh natural gas fired)	3.22	1.20	0.39	5.83
Log(variance, cost per MWh oil fired)	3.77	1.24	1.18	6.63
Log(variance, daily maximum temperature within country)	2.66	0.71	0.24	4.19
Log(population – millions)	2.68	1.27	1.35	5.74
Log(GDP – trillions, 2014 USD)	-0.53	1.33	-2.96	2.74
Log(CO_2 emissions – billion metric tons)	-1.94	1.45	-3.33	1.80
Total wind generation capacity (GW)	4.28	8.09	0.01	46.38
Total solar PV generation capacity (GW)	0.73	2.49	0	24.18
FIT payments by fuel (USD/KWh)				
Wind	0.05	0.07	0	0.33
Solar PV	0.18	0.25	0	0.88
Biomass	0.05	0.08	0	0.40
Geothermal	0.08	0.19	0	1.08
Ocean/tidal	0.05	0.19	0	1.08
RPS requirement (percentage)	1.76	4.08	0	18.2
Change in RPS requirement from same quarter, previous year	0.16	0.43	0	2.3

NOTE: (i) Total number of quarterly observations is 519. (ii) The means for FIT and RPS are interpreted as the fraction of total quarterly observations for which each policy was in effect. (iii) All monetary values expressed in constant 2010 USD, unless otherwise noted.

4.3. Regressions

We use ordinary least squares (OLS) to estimate the following regression equation:

$$V_{i,s} = \beta^{FIT} FIT_{i,s} + \beta^{RPS} RPS_{i,s} + \delta X_{i,s} + \eta Z_{i,s-4} + \alpha_i + \theta_s + \gamma_y + \varepsilon_{i,t}, \qquad (2)$$

where $FIT_{i,s}$ and $RPS_{i,s}$ are the policy dummies, α_i are country fixed effects, θ_s are quarterly fixed effects,[15] and γ_y are year fixed effects. $X_{i,s}$ is a vector of quarterly control variables. $Z_{i,s-4}$ a vector of (same quarter, previous year) lagged variables.

[15] More accurately, θ_s are seasonal fixed effects—we switch Q1-Q3 and Q2-Q4 for countries in the southern hemisphere.

First, because natural gas (predominantly) and oil are typically seen as the marginal fuels in electricity generation, the contemporaneous variation in their market prices should affect the variation in the wholesale price of electricity. To capture this, we compute the cost per MWh of natural gas- and oil-fired electricity at the prevailing daily spot prices using the relevant conversion factors, and calculate the (log) quarterly variances of each.[16] We use daily Brent crude oil and Henry Hub natural gas spot prices, as we consider these to be reasonable global benchmark prices for each resource. Second, we control for the effect of temperature-related demand shocks by including the (log) quarterly variance in country i's daily maximum temperature.[17] Third, potential socio-economic effects related to economy size and population are captured by log(GDP) and log(population). Fourth, to control for possible effects related to other carbon emissions reduction policies (for example, emissions trading schemes), we include log(CO_2 emissions).

Our lagged explanatory variables are as follows. First, as solar PV and wind generation are the two predominant RES-E technologies, greater capacity already in place should reduce the supply curve effect of either support policy. On the other hand, it should increase the fixed-price effect of FIT policy on the variance in electricity expenditures, because a higher proportion of generation would be receiving the FIT payment. We thus include (lagged) total solar PV and wind generation capacities. Because the level of capacity investment is in part endogenously determined by the support policy, to circumvent the clear endogeneity issue we use lagged values. Alternatively, to examine the effects of specific policy characteristics, we include the FIT payments to solar PV and wind. FIT payments in period t are embedded in our calculation of $V_{i,s}$, so we naturally wish to avoid having an embedded component of our dependent variable on the right-hand side of our regression equation—hence the use of a lag.

Finally, we examine the effect of a change in the RPS requirement to capture the incremental effect of increased stringency in RPS policy on new investment in RES-E

[16] The conversion factors are 10.1 Mcf per MWh for natural gas and 1.75 barrels per MWh for oil. Source: EIA http://www.eia.gov/tools/faqs/faq.cfm?id=667&t=2

[17] Daily maximum 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).

generation. The intuition here is related to the idea of a binding versus non-binding RPS (Shrimali and Kniefel 2011).[18] By isolating the incremental RPS requirement, we are able to better observe the true incremental quarterly supply curve effect of the RPS, as opposed to the cumulative effect, which may in some cases include preexisting RES-E capacity.

4.4. Estimation Results

Table 3 presents our estimation results. We find a robust, statistically significant reduction in the variance of electricity expenditures per unit under both FIT and RPS, which we consider to be convincing evidence of the supply curve effect hypothesized in Section 3. Moreover, our estimates consistently suggest FIT has a qualitatively stronger effect in suppressing expenditure risk per unit due to the fixed-price effect, although for each specification we are unable to reject the null hypothesis that the estimated FIT and RPS coefficients are statistically equivalent.[19] The key implication of this result is an additional benefit emanating from RES-E support policies that to our knowledge has been previously overlooked in the economic and policy literature. Specifically, retail electricity providers face more stable wholesale prices in the short run the greater is RES-E generation capacity. Thus, incentive schemes such as FIT and RPS/REC that boost investment in RES-E generation reduce risk not only for investors but also throughout the electricity market as a whole. This reduction in short-run price risk is likely to lead to lower risk premiums passed on to electricity consumers and fewer resources devoted to risk management strategies such as hedging and futures trading, in addition to a potentially lower equilibrium wholesale price as shown by Sáenz de Meira *et al*. (2008).

A second, subtler implication relates to economic welfare and the costs ofmeeting peak demand. Our result, combined with that of Sáenz de Meira *et al*. (2008), suggests that as support policies stimulate greater RES-E generation, the most expensive 'peaker'

[18] For example, say an RPS requirement of 10 percent is implemented in a country that already generates 12 percent of its supply from RES-E. The RPS would be non-binding, because no new renewable generation would need to be installed to meet the requirement. Shrimali and Kniefel (2011) in fact find a negative effect of RPS on RES-E penetration at the US state level. This is because many states consider existing RES-E capacity as eligible under the policy, undermining the promotion of investment in new capacity.

[19] For model (4), we are able to reject the null of equivalence at roughly 85% confidence.

Table 3. OLS estimates.

Variable	(1)	(2)	(3)	(4)	(5)
FIT (any fuel)	-0.52**	-0.59**	-0.59**	-0.58**	-0.63***
	(0.19)	(0.20)	(0.19)	(0.18)	(0.17)
RPS	-0.48***	-0.40***	-0.39***	-0.32**	-0.31
	(0.11)	(0.09)	(0.09)	(0.09)	(0.22)
Log(variance, cost per MWh natural gas fired)	0.16***	0.16***	0.16***	0.24***	0.29***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)
Log(variance, cost per MWh oil fired)	0.10	0.10	0.10	0.12	0.07
	(0.08)	(0.08)	(0.08)	(0.07)	(0.05)
Log(variance, daily maximum temperature)			0.06	0.13	0.05
			(0.07)	(0.07)	(0.13)
Log(population)		11.50	11.00	7.98	6.80
		(7.99)	(8.05)	(6.88)	(11.42)
Log(GDP)		-0.57	-0.52	-1.15	-0.12
		(1.04)	(1.05)	(0.68)	(1.25)
Log(CO_2 emissions)		0.14	0.10	0.04	0.19
		(1.53)	(1.56)	(1.71)	(1.61)
Total wind generation capacity †				-0.02	
				(0.01)	
Total solar PV generation capacity †				-0.08	
				(0.05)	
FIT payment to wind †					-0.99
					(0.58)
FIT payment to solar PV †					-1.49
					(3.21)
Change in RPS requirement					-0.06
					(0.20)
Constant	3.42***	-31.65	-30.19	-22.00	-11.03
	(0.38)	(25.85)	(26.02)	(22.07)	(28.99)
Number observations	519	519	519	500	445
R^2	0.58	0.58	0.58	0.61	0.60

NOTES: All models include country, year, and quarter fixed effects with robust standard errors clustered at the country-group level. †Indicates lagged value. * p<0.10, ** p<0.05, *** p<0.01

plants – *i.e.*, those at the steepest section of the conventional electricity supply curve – are less likely to be needed in the event of an unusually intense positive demand shock. Greater RES-E generation suppresses the transfer of economic surplus from consumers to producers when such demand spikes occur under a deregulated power market regime. Suppliers capture fewer windfall profits, because positive demand shocks do not result in concomitant wholesale price shocks that are as severe as they might otherwise be without RES-E generation.

To get a better sense of what our estimates imply in terms of magnitudes, consider the following back-of-the-envelope calculations. From Table 2, the sample mean of

$\log\left(var[\hat{P}_{i,t\epsilon s}]\right)$ is 4.56, which translates to a variance of $\exp(4.56) = 95.58$ and a standard deviation of 9.78 USD/MWh. If implementing a FIT reduces $\log\left(var[\hat{P}_{i,t\epsilon s}]\right)$ by 0.6, this implies nearly a 45 percent reduction in variance to $\exp(3.96) = 52.46$, which is roughly a 26 percent reduction in the standard deviation to 7.24 USD/MWh.[20] Similarly, if implementing an RPS reduces $\log\left(var[\hat{P}_{i,t\epsilon s}]\right)$ by 0.4, the variance in electricity expenditures per unit is reduced by about 33 percent to 64.07, and the standard deviation is reduced by 18 percent to 8.00 USD/MWh. These are clearly non-trivial reductions, implying the distribution of electricity expenditures per unit tightens considerably as a result of the additional RES-E generation stimulated by these support schemes.

Examining our other coefficient estimates, we find – not surprisingly – that the quarterly variation in the cost per MWh of natural gas-fired electricity is a strong determinant of the variation in per-unit electricity expenditures. The variance in the cost per MWh of oil-fired electricity has no statistically significant effect, which likely reflects the relatively sparse use of oil in our sample of countries as a fuel for electricity generation. No coefficient estimate for any other covariate—variations in temperature, GDP, population, CO_2 emissions, RES-E capacities, or specific policy features (FIT payments and RPS requirements)—is statistically significant. It is clear from the R-squared values for each regression model that adding these covariates does not improve overall explanatory power. The unexplained variation in $\log\left(var[\hat{P}_{i,t\epsilon s}]\right)$ may be due to random events such as unobservable transmission constraints, negative supply shocks, or any number of other factors.

4.5. Isolating the Supply-Curve Effect

To provide additional support for our main hypothesis, we run the exact same regressions presented in Table 3, except we use (log) quarterly variance of the wholesale electricity price as the dependent variable. This allows us to isolate the supply-curve effect as the dominant factor in reducing the short-run variance in total electricity expenditures per

[20] As a mathematical curiosity, the percentage changes in variance and standard deviation are uniform regardless of the starting point. To see this, one can simply repeat the exercise for a reduction of 0.6 in $\log\left(var[\hat{P}_{i,t\epsilon s}]\right)$ from both the minimum and maximum values in Table 2; the reduction in variance is 45 percent and the reduction in standard deviation is 26 percent in either case.

unit. Also, comparison to the coefficient estimates in Table 3 gives us some idea of the magnitude of the fixed-price effect for FIT. A third advantage is that it eliminates any concern that our results are somehow being driven by some other factor related to our construction of the daily generation-by-fuel data, because in this case they in no way enter into the realized value of the dependent variable.

Table 4 presents these results, which are entirely consistent with our two hypotheses, given the results in Table 3. The coefficients are essentially identical for RPS. For FIT the coefficient estimates are between 0.04 and 0.1 lower (in absolute value) than their counterparts in Table 3, implying the majority of the reduction in electricity expenditure risk under FIT is related to the supply-curve effect, with an additional reduction likely resulting from the fixed-price effect. Note, however, that the coefficient estimates for RPS are still slightly lower than those for FIT. One explanation for this might be that because RES-E generation is not uniformly distributed throughout the day, our calculation of daily expenditures on RES-E under RPS overestimates aggregate expenditure per unit and therefore variance for country-quarters with an RPS.[21] As a result, our estimates of the effect of RPS are potentially biased toward zero.

In terms of magnitudes, this means that for the 45 percent reduction in electricity expenditure variance associated with a coefficient of 0.6 on FIT in Table 3 calculated above, the supply-curve effect accounts for roughly a 40 percent percentage point reduction and the fixed-price effect the other 5 percentage points. For the associated 26 percent reduction in standard deviation, roughly 22 percentage points is attributable to the supply-curve effect, and 4 percentage points to the fixed-price effect. Given these results, we are confident that we have identified the supply-curve effect as the main source of the reduction in the short-run variance of electricity expenditure per unit related to the implementation of a RES-E support policy.

[21] Wind power, for example, is known to receive a generally lower average payment than other fuels precisely because spot prices are lower (possibly negative) when wind power overloads the system (Lively 2009). If the requisite data were available, the use of an intraday weighted-average for wind might alleviate this issue. Note that the same issue does *not* arise under FIT, as the price paid to wind is fixed.

Table 4. OLS estimates. Dependent variable: $\log(var[P_{i,t\epsilon s}])$.

Variable	(1)	(2)	(3)	(4)	(5)
FIT (any fuel)	-0.46*	-0.51*	-0.51*	-0.48*	-0.58**
	(0.23)	(0.24)	(0.24)	(0.23)	(0.21)
RPS	-0.42***	-0.41***	-0.40***	-0.32***	-0.36
	(0.12)	(0.11)	(0.11)	(0.11)	(0.25)
Log(variance, cost per MWh natural gas fired)	0.16***	0.16***	0.15***	0.23***	0.29***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.05)
Log(variance, cost per MWh oil fired)	0.10	0.10	0.09	0.11	0.06
	(0.08)	(0.08)	(0.08)	(0.07)	(0.04)
Log(variance, daily maximum temperature)			0.04	0.09	0.01
			(0.06)	(0.06)	(0.13)
Log(population)		8.56	8.26	6.85	4.13
		(6.74)	(6.76)	(6.20)	(10.12)
Log(GDP)		-0.46	-0.43	-1.28	-0.08
		(1.11)	(1.12)	(0.79)	(1.31)
Log(CO_2 emissions)		-0.43	-0.46	-0.58	-0.18
		(1.40)	(1.43)	(1.65)	(1.52)
Total wind generation capacity †				-0.03	
				(0.02)	
Total solar PV generation capacity †				-0.06	
				(0.05)	
FIT payment to wind †					1.48
					(2.90)
FIT payment to solar PV †					-1.08
					(0.62)
Change in RPS requirement					-0.05
					(0.20)
Constant	3.24***	-23.29	-22.40	-19.34	-6.26
	(0.42)	(22.00)	(22.06)	(20.02)	(25.96)
Number observations	519	519	519	500	445
R^2	0.59	0.59	0.59	0.61	0.60

NOTES: All models include country, year, and quarter fixed effects with robust standard errors clustered at the country-group level. †Indicates lagged value. * p<0.10, ** p<0.05, *** p<0.01

5. Testing for Possible Long-Run Effects

So far we have examined the effects of RES-E support schemes on the short-run variation in aggregate electricity expenditures per unit. What can be said about possible long-run effects? Does FIT or RPS lead to a greater long-run reduction in electricity expenditures per unit? To answer this question, we begin by reviewing the prediction of Schmalensee's (2012) model of long-run electricity expenditure risk under FIT and RPS.

5.1. Schmalensee's Model of Long-run Electricity Expenditure Risk

Our empirical findings for short-run effects are in contrast to a theoretical conclusion by Schmalensee (2012). He argues that although FIT shields investors in RES-E generation from price risk, "Measures that remove market risk from one set of players may simply shift it to others and not reduce the risk to society as a whole." He demonstrates using a highly stylized long-run model that the variance in total electricity expenditures may be greater under FIT than under RPS. However, this result and conclusion are reliant upon several strong assumptions that we argue are unlikely to hold in the real world. Let us say at once that our motive here is in no way to disparage Dr. Schmalensee's work on this topic (quite the opposite is true, in fact; his model inspired us to dig deeper into the issue and provided us with a clear research question, and for that we are grateful). With this disclaimer duly submitted, we offer the following critique of the assumptions supporting the assertion that the long-run variance in total electricity expenditures may be greater under FIT than under RPS.

First, the model assumes a fixed demand load and fixed conventional generation plant. Aside from the empirical impossibility of testing the model directly (because demand load varies both over time and across markets), these two assumptions together imply (i) renewable generation automatically displaces conventional generation; and (ii) the average cost of conventional electricity automatically rises with greater renewable penetration.[22] In reality, demand load increases over time in nearly all markets; it is thus entirely possible that renewable generation is added over time while conventional generation remains constant or even increases. It follows that the average cost of conventional electricity would be unaffected by greater renewable penetration. In the event that investment in renewable generation outpaces growth in demand load such that conventional generation is displaced, over the *long-run* the natural result would be that conventional generation plant is retired, thereby reducing average cost.

The second questionable assumption is essential to Schmalensee's result. The model assumes the long-run incremental cost of renewable generation[23]—which by

[22] Defined as the ratio of renewable generation to conventional generation.

[23] Included in this measure is the marginal rise in the unit cost of conventional electricity brought about by greater renewable penetration, which we have already argued is not guaranteed under more realistic assumptions.

definition depends on the fixed cost of capacity—is constant and always greater than the incremental cost of conventional generation. In practice, long-run incremental cost is reflected in the levelized cost per unit, a standard metric for comparison of cost competitiveness across technologies.[24] It is well-known that levelized costs for major renewable technologies like wind and solar have declined precipitously over the past two decades—a trend likely to continue. For example, the U.S. Energy Information Administration (2011) forecasts that the levelized cost per kWh for wind will be lower than that of coal by 2020. Moreover, in the *very* long run as global stocks of fossil fuels like coal and natural gas are exhausted, convex extraction costs and ever-increasing scarcity rents will drive the incremental cost of conventional electricity generation far above that of nearly all renewables.

Third, Schmalensee's is a static model in which the FIT payment and RPS requirement do not change over time. In reality, RPS requirements generally increase over time (see Figure 2), whereas FIT payments are digressed and are subject to periodic review and revision (as explained in Section 2.1). This latter feature of FIT policy is important because in the model's key analytical result the variance in electricity expenditures under FIT is increased further relative to RPS when the renewable supply curve is flatter. Intuitively, a flatter supply curve implies the quantity of renewables is more responsive to cost shocks when price is fixed. Such cost shocks are precisely the impetus for including a tariff review and revision clause in FIT policy.

Based on the above concerns, it is unclear as to whether we should expect the long-run variance in electricity expenditures to be greater under FIT than under RPS. A more fundamental question remains, however: Is long-run risk more important for electricity expenditures than short-run risk? Not necessarily. Future expenditures should be discounted using constant market discount rates; it is not clear why stakeholders with rational time preference would care more about long-run electricity expenditure risk than short-run. Investors have a longer-term view than consumers, but only for as long as it takes to earn the desired return-on-investment. Arguably, it is short-run electricity expenditure risk that has the most significant impact on stakeholder behavior, even when

[24] As a caveat, Joskow (2011) argues that levelized cost is a flawed metric by which to compare intermittent generation technologies with "dispatchable" technologies like coal and natural gas, because it incorrectly treats the two as a homogenous product governed by the law of one price.

it comes to long-lived infrastructure investments or the policy instruments designed to incentivize them. For these reasons, we submit that measuring the effects of RPS and FIT on short-run electricity expenditure risk provides a more immediately useful insight into the economic and practical implications of either policy. Nonetheless, in what follows we provide a test (albeit a limited one, due to data constraints) of the long-run effects of FIT and RPS policy on the variance of electricity expenditure per unit.

5.2. Basic Empirical Test of Long-Run Effects

From Figure 2 it is somewhat clear that when countries have no RES-E support policy (like New Zealand, for instance) the quarterly variance in electricity expenditures per unit seems to be rising over time. Conversely, when countries have a FIT in place, the quarterly variance appears generally to be falling over time. When countries have an RPS or both RPS and FIT concurrently, there is no obvious trend. This gives us a simple, intuitive way to test for the long-run effects of either policy. The test proceeds in two stages.

In the first stage, we begin by parsing our full sample of (log) quarterly variances for each country into four categories of subsamples: 1) intervals over which a country had no policy (NO_POL); 2) intervals over which a country had a FIT only; 3) intervals over which a country had an RPS only; and 4) intervals over which a country had both a FIT and an RPS (FIT_RPS). For example, from Figure 2 we see that New Zealand has one long interval in our sample of no policy, whereas Sweden has an interval of FIT only, an interval of both FIT and RPS, and an interval of RPS only. We repeat this exercise for every country in our sample, which gives us a total of 24 distinct country-policy intervals, as summarized in Table 5.[25] We then run the following regression *separately* for each country (i):

$$\begin{aligned} V_{i,s} = \beta_i^{NO\_POL} &+ \beta_i^{FIT} FIT_{i,s} + \beta_i^{RPS} RPS_{i,s} + \beta_i^{FIT\_RPS} FIT\_RPS_{i,s} \\ &+ \gamma_i^{NO\_POL} T_s + \gamma_i^{FIT} FIT_{i,s} T_s + \gamma_i^{RPS} RPS_{i,s} T_s \\ &+ \gamma_i^{FIT\_RPS} FIT\_RPS_{i,s} T_s + \delta X_{i,s} + \theta_s + \eta_{i,s}, \end{aligned} \tag{3}$$

[25] Hungary is dropped, as there are too few quarters within our sample for any meaningful inference to be made. For Denmark, the two separate intervals of FIT are counted as one.

Table 5. List of distinct country-policy intervals (within sample).

Observation	Country	Policy	Interval
1	Australia	FIT_RPS	2011Q1 – 2011Q4
2	Austria	FIT	2006Q1 – 2011Q4
3	Belgium	FIT	2006Q1 – 2011Q4
4	Canada	NO_POL	2003Q2 – 2008Q4
5	Canada	FIT	2009Q1 – 2011Q4
6	Czech Republic	FIT	2008Q1 – 2011Q4
7	Denmark	FIT	2000Q1 – 2002Q4, 2009Q1 – 2011Q4
8	Denmark	NO_POL	2003Q1 – 2008Q4
9	Finland	NO_POL	2000Q1 – 2010Q4
10	Finland	FIT	2011Q1 – 2011Q4
11	France	FIT	2006Q1 – 2011Q4
12	Germany	FIT	2006Q1 – 2011Q4
13	Netherlands	FIT	2006Q1 – 2011Q4
14	New Zealand	NO_POL	2000Q1 – 2011Q4
15	Norway	NO_POL	2000Q1 – 2011Q4
16	Poland	RPS	2010Q3 – 2011Q4
17	Spain	FIT	2006Q1 – 2011Q4
18	Sweden	FIT	2000Q1 – 2005Q4
19	Sweden	FIT_RPS	2003Q1 – 2005Q4
20	Sweden	RPS	2006Q1 – 2011Q4
21	Switzerland	FIT	2006Q1 – 2011Q4
22	United Kingdom	FIT_RPS	2010Q1 – 2011Q4
23	United States	RPS	2002Q1 – 2005Q4
24	United States	FIT_RPS	2006Q1 – 2011Q4

where $FIT_{i,s}, RPS_{i,s}$, and $FIT\_RPS_{i,s}$ are binary indicator variables that take the value "1" if in quarter s country i had (respectively) a FIT, an RPS, or both FIT and RPS. These indicator variables are then interacted with a simple quarterly trend (T_s).[26] $X_{i,s}$ are quarterly covariates and θ_s are seasonal fixed effects.

From these regressions, the coefficient estimates in which we are interested are $\hat{\gamma}_i^{NO\_POL}$, $\hat{\gamma}_i^{FIT}$, $\hat{\gamma}_i^{RPS}$, and $\hat{\gamma}_i^{FIT\_RPS}$—*i.e.*, estimates of the trends in (log) quarterly variance in electricity expenditures per unit for each of the 24 country-policy intervals

[26] Note that β_i^k and γ_i^k $(k = NO\_POL, FIT, RPS, FIT\_RPS)$ are identified only when country i has policy k over some portion of our sample period. For instance, if a country has only FIT over the entire sample, this means only β_i^{FIT} and γ_i^{FIT} are identified in (3).

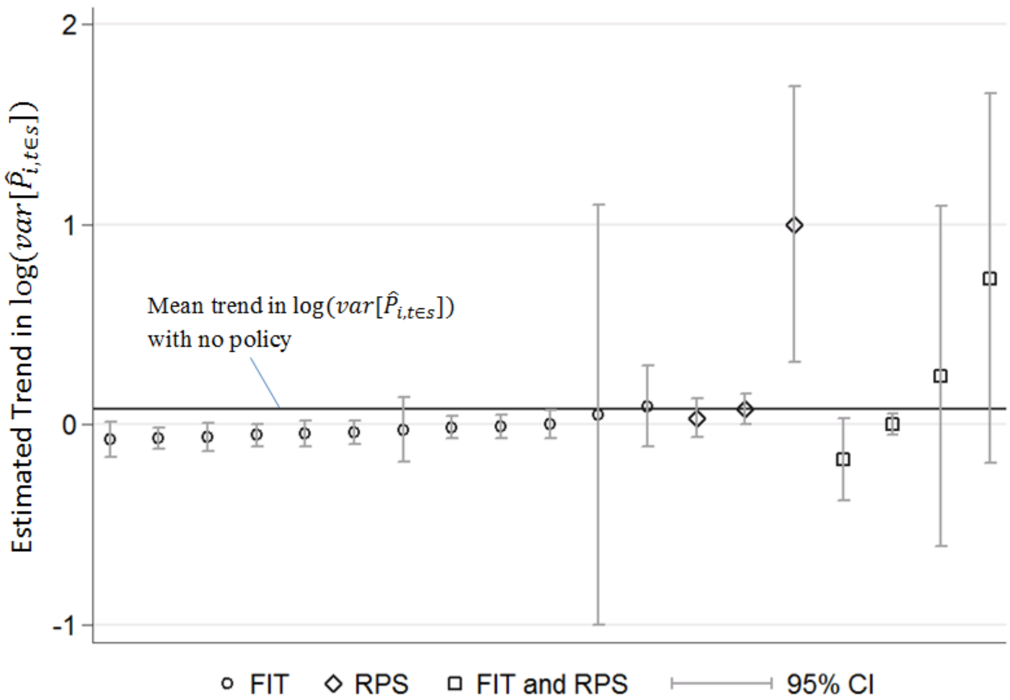


Figure 3. Estimates of trend in $\log(var[\hat{P}_{i,t\in s}])$ for each country-policy interval (see Table 5).

listed in Table 5. Figure 3 displays these estimates. As a benchmark, we show the *mean* estimated trend across the five country-policy intervals with no RES-E support policy.

From Figure 3 it is clear that compared to countries with no policy, countries with a FIT seem to experience a decline over time in the quarterly variance in electricity expenditures per unit, whereas for countries with either an RPS or both policies combined the results are mixed. The second stage of our long-run analysis is thus to regress the estimated trends on a set of policy indicator variables:

$$\hat{\mathbf{\Gamma}} = \varphi^{NO\_POL} + \varphi^{FIT}FIT_i + \varphi^{RPS}RPS_i + \varphi^{FIT\_RPS}FIT\_RPS_i + \mu_i, \qquad (4)$$

where $\hat{\mathbf{\Gamma}}$ is a column vector of the estimates $\hat{\gamma}_i^{NO\_POL}$, $\hat{\gamma}_i^{FIT}$, $\hat{\gamma}_i^{RPS}$, and $\hat{\gamma}_i^{FIT\_RPS}$ for each of the 24 country-policy intervals in Table 5. Regression equation (4) represents a simple t-test of means.

One issue with estimating (4), however, is that $\hat{\mathbf{\Gamma}}$ is automatically heteroskedastic because each element is itself an estimate with its own unique level of precision. Hanushek (1974) proposed FGLS as a solution to this 'estimated dependent variable' problem. Lewis and Linzer (2005) improved on the Hanushek FGLS procedure, however their method does not ensure a positive estimate of the variance of the regression. In fact, this turned out to be an issue in our estimation. We therefore followed their alternative suggestion of using Efron standard errors (Efron 1982). Lewis and Linzer showed using monte carlo simulations that Efron standard errors performed nearly as well as their FGLS standard errors and are likely to produce conservative estimates.

Table 6 presents the results of our second stage, using various combinations of additional control variables to estimate $\hat{\Gamma}$ in the first stage. To the extent that these estimates are representative of long-run trends in the variance of quarterly electricity expenditure per unit that occur under each policy, it is clear that only countries with a FIT experience a statistically significant reduction in per-unit electricity expenditure risk over time. RPS appears to have no effect, whereas the results are mixed for countries with both FIT and RPS simultaneously.

As in our short-run analysis, the results of our long-run estimation procedure stand in contrast to Schmalensee's (2012) conclusion that RPS may lead to a lower long-run variance in total electricity expenditures than FIT. If, as our estimates suggest, the quarterly variance in per-unit expenditures declines over time with FIT but not with RPS, then with a fixed demand load (a key assumption of Schmalensee's model) it follows that long-run total electricity expenditure risk would be unlikely to be lower under FIT than under RPS. However, we are careful here not to claim that our long-run results are not definitive evidence. Given the limited sample period of our dataset, one might reasonably argue that we do not have sufficiently long time series in stage one or enough observations of trends in stage two to interpret these estimates as true long-run effects. It is thus with great caution that we claim to be able to extrapolate trustworthy conclusions about RES-E policy effects on long-run trends in per-unit electricity expenditure risk, despite the rather strong statistical significance of the FIT and no-policy estimates.

6. Conclusion

The goal of this research has been to examine empirically the effect that economic support policies for renewable-energy-source electricity (RES-E) generation have on the variation in wholesale electricity expenditures per unit. We offered a simple theoretical

Table 6. Estimated effects of RES-E policies on the long-run trend in log($var[\hat{P}_{i,t\in s}]$).

	(1)	(2)	(3)	(4)	(5)	(6)
FIT	-0.13***	-0.10***	-0.09***	-0.11***	-0.16***	-0.14***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.06)
RPS	0.06	0.30	-0.02	-0.03	-0.30	-0.25
	(0.10)	(0.39)	(0.03)	(0.03)	(0.33)	(0.27)
FIT and RPS	-0.03	0.13	-0.47	-0.31	-0.28***	-0.26***
	(0.14)	(0.23)	(0.40)	(0.20)	(0.02)	(0.04)
No policy	0.08***	0.07***	0.07***	0.08***	0.14***	0.14***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.03)
Control variables in first-stage						
Log(variance, cost per MWh natural gas fired)		X	X	X	X	X
Seasonal fixed effects			X	X	X	X
Log(variance, cost per MWh oil fired)				X	X	X
Log(variance, daily maximum temperature)					X	X
Log(GDP)						X
Observations	24	24	22	22	21	21
R^2	0.34	0.29	0.40	0.47	0.46	0.27

Efron standard errors reported. * p<0.10, ** p<0.05, ***p<0.01

demonstration that such policies should reduce this variation – and, by association, wholesale price risk faced by electrical utilities – primarily because greater RES-E shifts the conventional electricity supply curve outward, implying a stochastic demand curve intersects it at a flatter portion. This leads to a tighter distribution of equilibrium wholesale prices. As feed-in tariffs (FIT) and renewable portfolio standards (RPS) are arguably the two dominant RES-E support policies worldwide, we estimated the effect each of these policies has on the (log) quarterly variance in electricity expenditures per unit using an unbalanced panel dataset of 19 countries over the period 2000-2011. Our results support our main hypothesis. In addition, we find that FIT is likely to reduce the variance electricity expenditure per unit by more than RPS, which we argue is related to the fixed-price design.

This result is, to our knowledge, new to the literature. It demonstrates a previously overlooked benefit of RES-E support policies. As electricity markets have moved toward a deregulated structure, wholesale price variability has increased, spurring retail electricity providers to devote significant resources to risk management. The costs of such activity, and of the pure risk itself, are ultimately borne by electricity consumers. We have shown that any support policy that stimulates RES-E generation in the short-run is likely to reduce per-unit electricity expenditure risk to utility providers.

We have argued that the short-run variance in electricity expenditure per unit is the most relevant metric by which to measure risk in electricity markets. At any rate, it is the only one we are best able to measure given the available data. Additionally, in contrast to the case originally made by Schmalensee (2012), we find that the *long-run* variance in total electricity expenditures for a given load is unlikely to be greater under FIT than under RPS, to the extent that a simple time trend in short-run variance translates to long-run variance. Ultimately, a number of long-run factors that are not captured by our model cloud our inferential capabilities about long-run variability. More research is needed to study long-run behavior—we simply do not have detailed enough data for enough countries over a long enough time span to test the hypothesis definitively in a long-run setting.

In closing, we believe our results have relevance beyond just RES-E generation. A similar intuition holds for any source of electricity generation – for example, nuclear – that enters into the generation mix at the base and not at the margin. Shifting the conventional electricity supply curve outward should reduce the short-run variation in wholesale prices just the same. A worthwhile analogue of this study would be to examine whether greater nuclear generation capacity has a similar, statistically significant result on wholesale prices.

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Appendix

Table A1. Detailed list of data sources.

Data series	Source	Link	Status
Daily wholesale prices			
Austria; Belgium; Czech Rep.; France; Germany; Hungary; Netherlands; Poland; Spain; Switzerland; United Kingdom	Platts-McGraw Hill – Europe Power Daily	http://www.platts.com/products/market-data-electric-power	Purchased
Daily total generation			
Austria; Belgium; Czech Rep.; France; Germany; Hungary; Netherlands; Poland; Spain; Switzerland	European Network of Transmission System Operators for Electricity (ENTSOE)	https://www.entsoe.eu/data/data-portal/consumption/Pages/default.aspx	Publicly available
United Kingdom	UK National Grid	http://www2.nationalgrid.com/uk/Industry-information/Electricity-transmission-operational-data/Data-Explorer/	Publicly available
Daily wholesale prices & total generation combined			
Australia	Australian Energy Market Operator (AEMO)	http://www.aemo.com.au/Electricity/Data/Price-and-Demand/Aggregated-Price-and-Demand-Data-Files	Publicly available
Canada (Ontario)	Independent Electricity System Operator (ISEO) of Ontario	http://www.ieso.ca/Pages/Power-Data/default.aspx - report	Publicly available
Denmark; Finland; Norway; Sweden	Nordpool Spot	http://www.nordpoolspot.com/#/nordic/table	Purchased
New Zealand	EMI Electricity Authority	http://www.emi.ea.govt.nz/Datasets/Browse?parentDirectory=%2FDatasets%2FWholesale	Publicly available
USA (ISO-New England, PJM, and New York ISO)	ISO New England PJM New York ISO	http://www.iso-ne.com/ http://www.pjm.com/ http://www.nyiso.com/public/index.jsp	Publicly available
Renewable generation & capacities			
Generation – all renewables (annual level)	Int'l. Energy Agency –Renewables Information Reports (2002-2014)	http://www.oecd-ilibrary.org/statistics	Publicly available
CONT'D NEXT PAGE			

Wind speeds and Solar radiation (monthly level)	NASA Atmospheric Science Data Center	https://eosweb.larc.nasa.gov/cgi-bin/sse/global.cgi?email=skip@larc.nasa.gov	Publicly available
Wind generation capacity	Global Wind Energy Council (GWEC)	http://www.gwec.net/global-figures/interactive-map/	Publicly available
Solar generation capacity	European Photovoltaic Industry Association	http://solarpowereurope.org/	Purchased
Policy data			
FIT and RPS (all countries)	Johnstone *et al.* (2010)		Shared by N. Johnstone
Renewable Energy Credits (RECs)			
Australia	Australian Government Clean Energy Regulator	http://www.cleanenergyregulator.gov.au/	Publicly available
Poland	PolPX Monthly Market Reports	http://tge.pl/en/155/raporty-miesieczne	Publicly available
Sweden (2000-2004)	Swedish Energy Agency	http://www.iea.org/policiesandmeasures/pams/sweden/name-21727-en.php	Publicly available
Sweden (2005-2013)	Svensk Kraftmäkling (SKM)	http://skm.se/priceinfo/history/2014/	Publicly available
United Kingdom	ePower	http://www.epowerauctions.co.uk/trackrecord.htm	Publicly available
USA	Marex Spectron	http://www.marexspectron.com/	Purchased
Miscellaneous			
Daily temperatures	National Oceanic and Atmospheric Administration (NOAA)	http://gis.ncdc.noaa.gov/all-records/catalog/search/resource/details.page?id=gov.noaa.ncdc:C00861	Publicly available
Population; GDP; GDP deflator	World Bank Development Indicators Databank	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators	Publicly available
CO_2 emissions	U.S. Energy Information Administration	http://www.eia.gov/environment/data.cfm#intl	Publicly available
Exchange rates	FRED – St. Louis Fed	https://research.stlouisfed.org/fred2/	Publicly available