

Article

The Implications of Policy Uncertainty on Solar Photovoltaic Investment

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Abstract: Policy and electricity price uncertainty provide disincentives to investors considering renewable energy investments. While electricity price uncertainty impacts on investment decisions relating to any energy investment, whether renewable or non-renewable, policy uncertainty will affect renewable energy investment decisions to a far greater extent. In this study, we consider the two main sources of uncertainty a solar Photovoltaic (PV) project is exposed to: electricity price uncertainty and policy uncertainty. We focus our analysis on utility-scale solar photovoltaics in the Pennsylvania, Jersey, Maryland Power Pool (PJM) electricity market and the New Jersey Solar Renewable Energy Credit (SREC) market. Using Solar Renewable Energy Credits as a proxy for policy, we find that there is considerable volatility in both electricity prices and policy. In a sample covering eleven years, we implement univariate Generalized Autoregressive Conditional Heteroskedastic (GARCH) and combinations of GARCH models with different weighting schemes and find that combination models provide superior forecasts. In renewable energy markets, policy supports have a significant impact on an investment's profitability. The implication for policymakers is clear: to foster investment in solar PV, policy stability is critical.

Keywords: solar photovoltaics; volatility; investment; policy uncertainty; GARCH

1. Introduction

Described by the United Nations as “one of the most pervasive issues of our time”, climate change is an area that has attracted increasing attention in the literature. In order to mitigate the effects of environmental issues, divesting from fossil fuels and attracting investment to renewable sources of energy is essential. Notwithstanding the admirable advances in renewable energy technologies, to be a commercially viable option, most require some kind of policy support in order to garner investment, at least initially. While most studies rightly focus on the volatility of future electricity prices to accurately price the risk of investing in renewable energy, other sources of uncertainty are likely to also be of concern to potential investors (see for example [1]). In its 2020 Renewables Report [2], the International Energy Agency (IEA) find that policy certainty is key to attracting renewables. They suggest that whereas renewables have proved to be relatively unscathed by the Covid-19 pandemic, they are not resilient to policy uncertainties; and that both solar Photovoltaic (PV) and wind could be increased by an extra 25% each globally were countries to address policy uncertainties. Specifically, they note that the U.S. could achieve a much more rapid decarbonization of the U.S. power sector if solar PV and wind generation were supplemented with additional policy supports. Burns [3] considers the U.S. policy environment and finds evidence that higher policy uncertainty leads to lower investment in renewables.

Renewable energy projects have large upfront capital costs and generate revenue over a long period of time, often twenty or thirty years. For many renewable energy investments, much of the return to investors is generated from the policy supports in place, so investors must allow for the possibility that these incentives will not last (examples of policy support include subsidies, feed-in tariffs, green certificates, tax breaks, etc.). This will increase the required rate of return on such investments and lead to decreased investment. There are several examples of policy supports for renewable energy being abruptly changed or withdrawn. For example, Spain initiated a generous programme of subsidies for both solar and wind in 2004 but suddenly ended the scheme following the financial crisis, leading to heavy losses for investors. Similarly, the Czech Republic decreased feed-in tariffs by 26% and the green bonus by 28% for a three-year period between 2011 and 2013, affecting previously installed renewable energy projects. Greece initiated policy changes in 2012 imposing levies on both wind and solar of between 10% and 30%. Finland, France, Italy, and Bulgaria have also implemented policy changes that have affected previous installations. In many instances, this has seen bankruptcies as a direct result of the policy changes. Introducing changes such as these leads to an immediate increase in the risk premium associated with investing in these technologies thus decreasing the attractiveness of investment. Hence, it is important to factor in not only electricity price but also policy uncertainty when assessing renewable investment opportunities.

One of the most successful examples of a well-designed and comprehensive solar support scheme is the Solar Renewable Energy Credit (SREC) system in place in New Jersey, United States. Since its introduction, New Jersey's solar PV capacity has increased dramatically, going from less than 50 MW in 2007 to more than 2900 MW in 2019. The SREC is part of the nationwide Renewable Portfolio Standard (RPS) program. Its SREC system is the most mature in the U.S. and dates back to 2009. The RPS in New Jersey mandates electricity suppliers to produce a specific amount of electricity from solar energy (known as a "solar carve-out"): 4.1% by 2028. Suppliers have to comply with this solar carve-out by trading SRECs, which certify that the electricity produced derives from solar. Specifically, one SREC is issued when 1 MWh of electricity is generated from solar. SRECs are completely independent of the developers' electricity profits, therefore acting as a separate source of income for developers [4,5]. It is for this reason that SRECs are deemed a key factor in stimulating the solar industry in the U.S. [5,6].

In this study, we add to the literature by considering both electricity price uncertainty and policy uncertainty to price the risk of investing in utility-scale solar photovoltaic. We confine our analysis to the Pennsylvania, Jersey, Maryland Power Pool (PJM) electricity market and the New Jersey Solar Renewable Energy Credit (SREC) market. We implement a Generalized Autoregressive Conditional Heteroskedastic (GARCH) modelling approach to estimate the volatility of both electricity prices and policy. Our findings suggest that policy uncertainty is an extremely important factor when considering investing in solar photovoltaic and that failing to include policy uncertainty could lead to incorrect investment decisions. Further, investors who have concerns surrounding policy uncertainty are likely to seek higher returns due to increased risk of investment, thus reducing the overall investment into the very technologies that are essential to help address the negative impact of climate change. Therefore, it is up to policymakers to ensure appropriate, long-term, stable policy in areas they are seeking to attract renewable energy investment.

Assessing the feasibility of all types of renewable energy investment is becoming increasingly important. Traditionally, such investment opportunities have been evaluated using Discounted Cash-Flow (DCF) models that estimate expected revenue streams and discount them back to today using the weighted average cost of capital of the investment. In a comprehensive assessment of solar photovoltaic technologies, Sheik and Kocaoglu [7] observe that while many assessment methods have been established and developed in the renewable energy space, more extensive and efficient methodologies are required. Real option methodologies are now commonly suggested as a superior approach because this method allows for the value of flexibility as uncertainties reveal themselves over time, while the discounted cash flow approach is static in nature [8]. However, the valuation of renewable energy projects using a real options approach depends crucially on a reliable estimate of

the volatility of the future cash flows the project generates. In the absence of such a reliable estimate, the real option value will be inaccurate. The research question underlying this study is therefore the following: in order to implement valuation techniques that are often considered superior, how should one accurately estimate and forecast the volatility of the main sources of uncertainty?

In this study, we do just that by identifying the main sources of uncertainty, namely, policy uncertainty and electricity price uncertainty, and by choosing the best models or combinations of models to estimate both. This study is, to the best of our knowledge, the first to model both electricity price and policy volatility for utility-scale solar PV. The remainder of this study proceeds as follows: in Section 2, we discuss the background and related literature, in Section 3 we present methodology, and the data are presented in Section 4. Results and discussion are presented in Section 5, while Section 6 concludes.

2. Background and Related Literature

When making an investment decision, investors consider the cash flows the project will generate in the future and compare it with the cost of investing today. Any uncertainty surrounding the estimates of the future cash flows adds to the investors' perceived risk of investing in the project. The greater the perceived risk is, the higher the required rate of return the investor will demand to compensate for undertaking the uncertainty. The net cash flows from a solar energy project arise as a result of considering the total revenues the project will generate over its lifetime less the overall costs of the solar PV system. The total costs include upfront capital costs such as hardware costs, land costs, system design, and connection costs, as well as ongoing operational and maintenance costs. The ongoing operational and maintenance costs can be reliably estimated and thus have little volatility. The main sources of uncertainty with such projects are therefore confined to uncertainties surrounding the cash inflows associated with the project, so we focus our attention on these. The cash inflows arise as a result of the amount of electricity generated times the electricity price and any cash inflows that arise as a result of policy supports such as tax breaks and renewable energy credits. We proceeded by consulting previous literature to identify the main sources of uncertainty to the cash inflows of a solar energy project.

2.1. Electricity Price Uncertainty

The cash inflows generated by energy technologies depend crucially on the electricity price, and previous studies find that the primary source of volatility is due to changes in electricity prices. For example, Zhang et al. [9] examine the relationship between electricity prices and non-renewable energy cost and find evidence indicating that the uncertainty related to the costs of coal-fired generation is embedded in the electricity price uncertainty. The authors assume that the long-term price of electricity is equal to the non-renewable energy costs (the average cost of coal-fired generation). Torani et al. [10] also identify electricity prices as one of the main sources of volatility for solar energy. The volatility of the electricity price depends on various aspects of the electricity market: inelastic demand, high transportation costs, seasonal effects, non-storability, etc., and is dynamically very similar to the volatility of financial markets, as electricity is traded on competitive wholesale markets [11]. Electricity prices are also taken into account as a source of uncertainty for renewables by Monjas-Barroso and Balibrea-Iniesta [12], who analyse the mechanisms of public support for renewable energy. Similar work has been carried out by Boomsma et al. [13], who analyse investment timing for renewable energy projects under different support schemes, and Biondi and Moretto [14], who evaluate the uncertainties surrounding the Italian PV market. Given these findings, we included electricity price uncertainty in our analysis.

2.2. Policy Uncertainty

The second major source of volatility for investors that we considered was policy uncertainty. There is increasing evidence to suggest that policy uncertainty can be a significant deterrent to renewable energy investment. For example, Reuter et al. [15] find that the certainty of support levels

plays a considerable role in a producers' decision to adopt a technology. A major source of contention in the literature is how to model climate policy volatility. Several previous studies have opted for carbon price uncertainty to proxy for policy uncertainty [16,17]; while others such as Abadie et al. [18] take an alternative approach and model emission trading schemes. Deeney et al. [19] highlight the importance of considering the impact legislative decisions have on market participants' reactions by analysing the European Emissions Trading System (ETS). Other studies involve analysing specific areas of policy and affected sectors, such as [20], which models the effect of policy uncertainty in the agricultural industry by analysing the carbon tax, and [21], which models feed-in tariffs for renewable energy sources.

In the New Jersey market, two types of support policies are in place for solar PV plants. At the federal level, the Investment Tax Credit (ITC) allows developers to receive a specific percentage of their upfront costs in tax credits in the first year. For plants built in 2019, an amount equal to 30% of the upfront cost is received in tax credits, while a ramp-down schedule exists for plants built after 2019. The Investment Tax Credit is known and certain, so there is no uncertainty associated with this policy. At the state level, Solar Renewable Energy Credits (SRECs) are implemented as part of the Renewable Portfolio Standards (RPSs). SRECs represent the renewable features of solar generation, and one SREC represents proof that 1 MWh of electricity has been generated from solar. All electricity suppliers are obliged to use the SREC program to prove compliance with the RPS, by trading the certificates daily at regional level. SREC market participants are continually exposed to fluctuations in the prices of these certificates and profits generated from the trading of SRECs represent one of the major sources of income for solar developers. Hence, we confined our analysis to this policy uncertainty.

We used SREC prices as a proxy for policy uncertainty, a practice not uncommon in the literature. In a real options study of wind energy, Eryilmaz and Homans [1] model two sources of policy uncertainty: Production Tax Credits (PTCs) and Renewable Energy Credits (RECs) and find the investment decision is sensitive to both. Boomsma et al. [13] also model policy uncertainty for wind energy by looking at Renewable Energy Credits (RECs). Ioannou et al. [22] identify changes in Renewable Portfolio Standard targets as a source of risk for renewable energy investments, and Rodríguez et al. [23] recognize volatile prices of renewables certificates as a major source of uncertainty investors are exposed to. This is confirmed by Zeng et al. [24], who acknowledge that changing certificate prices will have a growing impact on the optimal investment timing decision. It has been noted by Felder and Lockley, and Mann [25,26] that volatility in SREC prices is greater than certificate volatility for other renewables, supporting our hypothesis that policy volatility in renewable energy investment is of considerable importance.

2.3. Modelling Volatility

To estimate the volatility of the two sources of uncertainty we have identified, we implemented a GARCH methodology, consistent with previous approaches. Examples can be seen in [27–32]. The time-varying volatility of energy markets has traditionally been estimated using different GARCH models (developed by [33], in addition to previous work by [34]), where the conditional variance is a deterministic function of past data and of the parameters of the model. Several empirical studies of the energy market use a GARCH(1,1) model ([35,36], for example). Simple models of GARCH(1,1) are considered very useful in estimating volatility, compared to more complicated multivariate GARCH models, as they converge fast to a quasi-maximum likelihood estimation and result in strong forecasting performance [11,37–39].

In this study, we considered not only individual GARCH models but also combinations of the individual models. The motivation to combine GARCH models derives from the absence of a single best model for forecasting volatility and the fact that many models perform similarly. Initially implemented by Bates and Granger [40], combining forecasts from different models has subsequently been applied extensively to electricity markets (see [41–50] as examples). (For the purpose of clarification, we applied

the GARCH model to estimate the volatility. Should we have needed to calculate the historical volatility, we would have applied the methodology outlined in [51]).

3. Methodology

3.1. GARCH Models

GARCH models are widely implemented across finance and economics, and many variations exist. Given our contention is that implementing alternative methods to traditional discounted cash flow models, such as real options models, will only lead to improved results if the volatility is accurately estimated, we considered several individual GARCH models, summarized in Table 1, and combinations of models, described in Section 3.2.

Table 1. Autoregressive Conditional Heteroskedastic (ARCH)-type models [30] (h_t denotes conditional variance, ω the constant, α the ARCH effect, and β the GARCH effect).

ARCH(1)	$h_t = \omega + \alpha \varepsilon_{t-1}^2$
GARCH(1,1)	$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$
GARCH-M	$r_t = \omega + \beta x_t + \theta h_t + \varepsilon_t$
PARCH	$h_t = \omega + \alpha \varepsilon_{t-1}^\phi + \beta h_{t-1}^{\phi/2}$
NGARCHK	$h_t = \omega + \beta h_{t-1} + \alpha_1 (\varepsilon_{t-1} - k_0)^2 + \alpha_2 (\varepsilon_{t-1} - k_0)^2$
IGARCH	$h_t = \omega + \alpha \varepsilon_{t-1}^2 + (1-\alpha)h_{t-1}$
SAARCH	$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1} + \beta h_{t-1}$
TGARCH	$h_t = \omega + \alpha \varepsilon_{t-1} + \gamma \varepsilon_{t-1} I(\varepsilon_{t-1} > 0) + \beta h_{t-1}$
GJR-GARCH	$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma I(\varepsilon_{t-1} < 0) \varepsilon_{t-1}^2$
APARCH	$h_t^{\delta/2} = \omega + \alpha (\varepsilon_{t-1} + \gamma \varepsilon_{t-1})^\delta + \beta h_{t-1}^{\delta/2}$
EGARCH	$\ln(h_t) = \omega + \alpha (\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} - \sqrt{2/\pi}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta \ln(h_{t-1})$

GARCH, Generalized Autoregressive Conditional Heteroskedastic. GARCH-M, GARCH in mean. PARCH, Power ARCH. NGARCHK, Nonlinear GARCH. IGARCH, Integrated GARCH. SAARCH, Simple asymmetric ARCH. TGARCH, Threshold GARCH. GJR GARCH, Glosten-Jagannathan-Runkle GARCH. APARCH, Asymmetric power ARCH. EGARCH, Exponential GARCH.

A mix of symmetric and asymmetric models were considered. Asymmetric models take account of the fact that negative news has a greater impact on conditional volatility than positive news [52]. This is referred to as the leverage effect and is denoted by γ . Before applying GARCH to the conditional variance equation, an autoregressive moving average (ARMA) model was applied for the conditional mean. All models were augmented by specifying different ARMA(p,q) models for the mean equations, where AR(p) refers to the autoregressive model of order p and MA(q) refers to the moving average model of order q. For electricity prices, an ARMA(2,1) was specified for the mean equation, with innovations following a Student’s t distribution, and a weekday dummy to take into account weekly periodicity. Utilizing a weekday dummy to account for short-term seasonality of electricity prices is a common approach, and examples can be seen in [30,53–55]. Dummy variables are preferred to alternative specifications when analysing seasonal behaviour due to their ease of interpretation and intuition [56]. Additionally, weekday dummy variables shed light on issues such as the “weekend effect”, where lower electricity prices can be spotted on weekends, observed in a number of studies (for example, [32,57]).

For SREC prices, an ARMA(0,1) was specified for the mean equation, with innovations following a normal distribution. A naïve model taking the form of an AR(1) was also included in the analysis to assure the superiority of the other models in terms of forecasting performance.

3.2. Weighted Average Forecast Combinations

We continued by developing combination schemes made up of all the individual models listed in Table 1. Six combination schemes were considered, in line with [47], and the aim was to assign weights w_{kt} to the individual K forecasts \hat{h}_{kt} to obtain a weighted forecast \hat{h}_t^c :

$$\hat{h}_t^c = \sum_{k=1}^K w_{kt} \hat{h}_{kt} \quad (1)$$

Simple and geometric averaging: We computed a simple arithmetic and geometric mean for all forecasts produced by the individual models. This methodology is commonly used in economic forecasting and is very robust, see for example [58–60], and [47]. For the geometric average computation, the simple average of the log of volatility forecasts is taken, and then the exponential of the average log volatility is taken.

$$\hat{h}_t^c = \frac{1}{K} \sum_{k=1}^K \hat{h}_{kt} \quad (2)$$

$$\hat{h}_t^c = \sqrt[K]{\prod_{k=1}^K \hat{h}_{kt}} \quad (3)$$

Inverse Root Mean Squared Error (IRMSE): We assigned weights to the different individual GARCH model forecasts by looking at the inverse of the Root Mean Squared Error (RMSE). The models producing the smaller RMSE will obtain higher weights compared to other models and therefore affect the final combined forecast in a greater way. We are essentially giving more weight to the models that perform best individually. The weights assigned to each individual model can be defined as follows:

$$w_{kt} = \frac{\frac{1}{RMSE_{kt-1}}}{\sum_{k=1}^K \frac{1}{RMSE_{kt-1}}} \quad (4)$$

where $RMSE_{kt}$ denotes the out-of-sample forecast performance of the individual models.

Principal Component Analysis (PCA): PCA is a statistical method that decreases data dimensionality by carrying out a covariance analysis between factors. Since many of the individual models are similar, PCA allows us to isolate the common variation of volatility. We took the first eigenvector of the variance–covariance matrix of the standardized forecasts as weights for each individual model.

Constrained Least Square (CLS): We regressed the volatility proxy (squared returns) on all volatility forecasts and obtained estimated coefficients for each model. The estimated coefficients were then used as weights for each individual model. Three constraints were applied to the ordinary least square estimation: the intercept is zero, all weights are positive, and the sum of the weights is equal to 1. The CLS regression was

$$\hat{\sigma}_t^2 = w_{0t} + \sum_{k=1}^K w_{kt} \hat{h}_{kt} + \eta_t \quad (5)$$

and the constraints were as follows:

$$w_{0t} = 0, w_{kt} > 0 \text{ and } \sum_{k=1}^K \hat{w}_{kt} = 1, \forall k, t \quad (6)$$

The forecasts were then calculated as

$$\hat{h}_t^c = \sum_{k=1}^K \hat{w}_{kt-1} \hat{h}_{kt} \quad (7)$$

Bayesian Model Averaging (BMA): BMA allows us to apply weights not only to different models but also to different combinations of models (increasing the possible combinations from 1 to 2^k). We used Raftery et al.'s [61] BMA package in R. The weights were computed as posterior probabilities for the regression of the volatility proxy on separate ensembles of individual forecasts.

$$w_{lt} = \frac{L(\hat{\sigma}_{t-1}^2 | m_l, D) \rho(m_l)}{\sum_{j=1}^{2^K} L(\hat{\sigma}_{t-1}^2 | m_j, D) \rho(m_j)} \quad (8)$$

where m_l represents a combination of models, and $L(\hat{\sigma}_{t-1}^2 | m_l, D)$ the log likelihood of m_l . For a more extensive explanation of the BMA combination method see [61].

3.3. Forecast Evaluation

To evaluate the forecast accuracy of the models and combinations of models we did not rely on a single measure of error, instead opting for various loss functions: the Mean Squared Error (MSE), the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and the Quasi-Likelihood (QLIKE) (see Equations (9)–(12), where h_t denotes the forecasted volatility and $\hat{\sigma}_t^2$ denotes the actual volatility). Zhang and Zhang [62] highlight the importance of not relying on a single loss function, as it is unclear which one is most suitable for the assessment of volatility models. Patton [63] suggests using both the MSE and QLIKE functions when utilizing an imperfect volatility proxy. The QLIKE measure is asymmetric in how it penalizes over- and under-prediction of volatility (under-prediction is heavily penalized), while the MSE focuses on point forecast accuracy. The MAE function is extremely robust to outliers; however it is influenced by the noise in the volatility proxy. The RMSE, simply the root of the MSE, is reported solely for reference as it is used in the computation of the IRMSE combination scheme.

$$MSE = \frac{1}{T} \sum_{t=1}^T (\hat{\sigma}_t^2 - h_t)^2 \quad (9)$$

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (\hat{\sigma}_t^2 - h_t)^2} \quad (10)$$

$$MAE = \frac{1}{T} \sum_{t=1}^T |\hat{\sigma}_t^2 - \hat{h}_t| \quad (11)$$

$$QLIKE = \frac{1}{T} \sum_{t=1}^T \log(h_t) + \frac{\hat{\sigma}_t^2}{\hat{h}_t} \quad (12)$$

4. Data

In order to forecast daily volatility for electricity and SREC prices, we focussed on the New Jersey area by applying the analysis to the Pennsylvania, Jersey, Maryland Power Pool (PJM) electricity market and to the New Jersey SREC market. Taking P_t as the price on day t , we carried out the analysis on the daily log price return r_t , defined in the following way:

$$r_t = \ln(P_t) - \ln(P_{t-1})$$

Since the underlying volatility is unobservable, we used daily squared log returns as a proxy, in accordance with previous studies (see, for example [64–68]). Squared log returns are an unbiased estimator for true volatility, as outlined in [68,69]. One-step ahead forecasts are produced for the two sources of uncertainties. Investors are constantly exposed to daily changes in electricity and SREC prices, and an accurate forecast of these daily changes will aid in taking long-term investment decisions. Day-ahead electricity price forecasting is at the centre of decision-making optimization for electricity market participants [70]. For example, as discussed in [71], companies hedge and bid against daily volatility in electricity prices in the short term for long-term risk management. In the literature, one-step ahead electricity price forecasts are common, and examples can be seen in [46,72,73], just to mention a few. Our sample ranges from January 2007 to January 2018, for a total of 4014 observations, with our out-of-sample period starting in January 2014 and comprising 1460 observations. (An out-of-sample period of 4 years is used to ensure that at least one-third of the sample is utilized for the out-of-sample forecast, in order to increase the robustness of the analysis).

We present the electricity log returns series in Figure 1. It is clear from the graph that the series is characterized by high volatility and spikes. Prices were obtained from the website of Engie. The PJM market in the United States is the largest market, covering fourteen states.

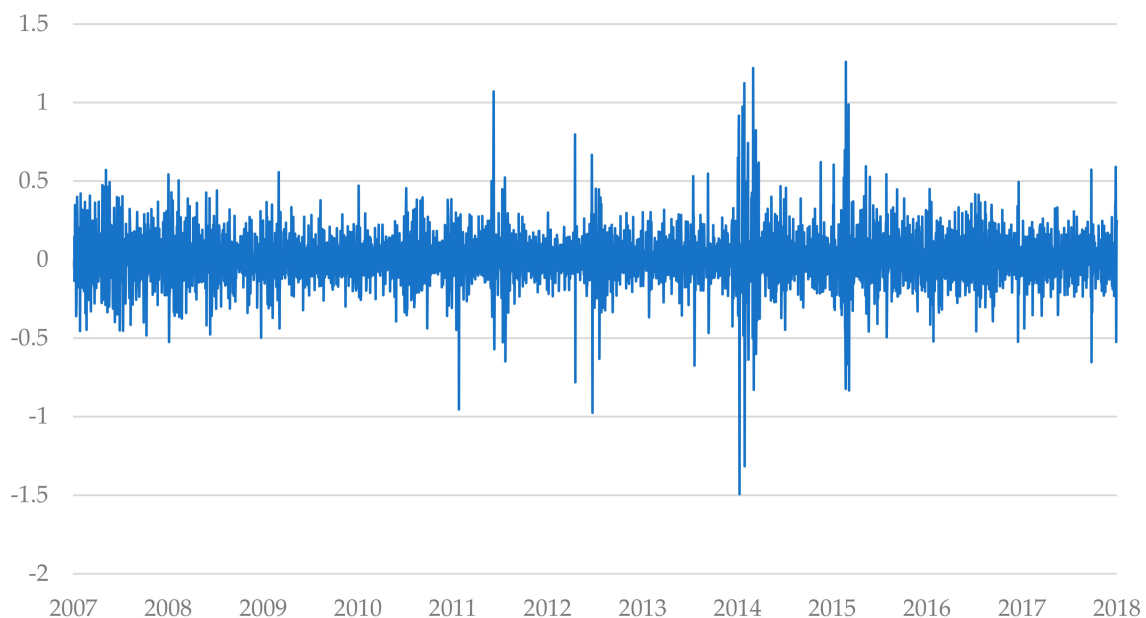


Figure 1. Pennsylvania, Jersey, Maryland Power Pool (PJM) electricity prices log returns.

SREC log returns are presented in Figure 2. We used New Jersey daily SREC prices since New Jersey is the oldest and most developed SREC market in the U.S. The data ranging from January 2007 to March 2016 were obtained from NJC Clean Energy, while the data from March 2016 to the end of the sample period were obtained from Bloomberg. As our dataset contains observations from two separate sources, we carried out a reduced sample analysis using only data from NJC Clean Energy, excluding data from March 2016 onwards for robustness purposes. The volatility in SREC prices reduced dramatically starting from March 2016, as can be seen in Figure 2, giving us a further reason to carry out the same analysis on the reduced sample. The decrease in SREC price volatility is likely linked to the extension of the solar Investment Tax Credit (ITC) at the end of 2015: a 30% three year extension and an additional subsequent two year ramp down [74]. This extension provided the solar industry in the U.S. with a more stable investment climate, thus explaining the decrease in volatility. As a further robustness test, the reduced sample analysis was carried out not only on SREC prices but also on electricity prices.

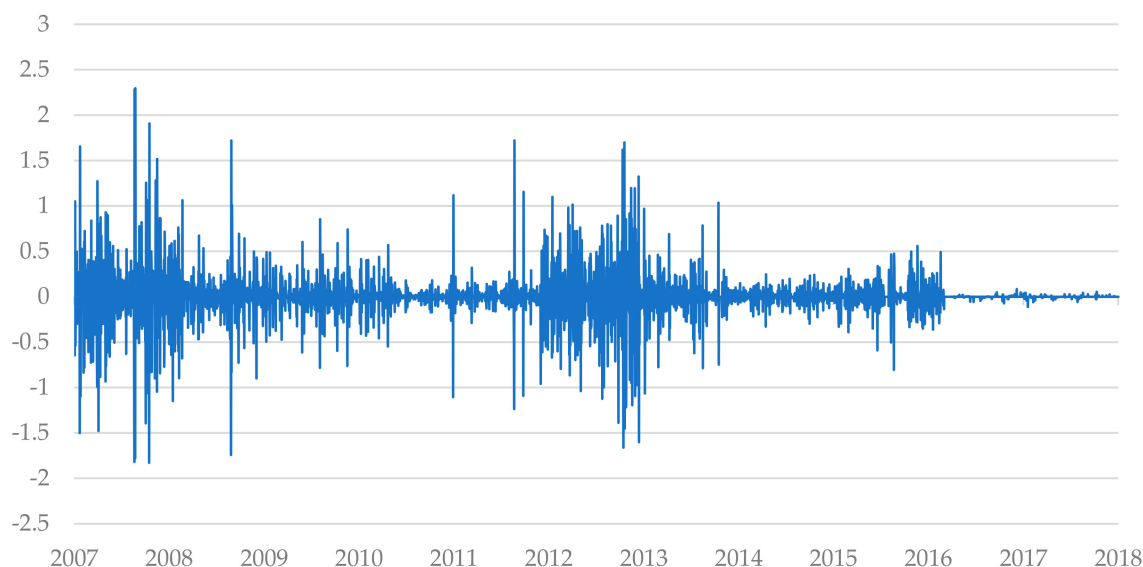


Figure 2. New Jersey Solar Renewable Energy Credit (SREC) prices log returns.

For both electricity prices and SREC prices, four years were left for the out-of-sample forecast comparison: the first year out-of-sample was used to initialize the weight estimations for the model combinations. As the forecast date progressed, the calibration window was enlarged to incorporate more data. The final three years out-of-sample were used for forecast comparison by computing loss functions for each combination scheme and each individual model. Refer to Table A1 for clarification, if needed.

Descriptive statistics for each log return series are provided in Table 2. The Skewness–Kurtosis test for normality tests the null hypothesis of normality and is rejected at the 1% level of significance for all series. The Augmented Dickey–Fuller (ADF) test tests for the presence of a unit root, as well as the Phillips–Perron (PP) test. Both the ADF and PP tests reject the null hypothesis of a unit root at the 1% significance level, implying that the series are stationary, an important assumption for time series analysis.

Table 2. Descriptive statistics of log returns.

	Electricity	SREC
Observations	4014	4015
Mean	0.0003	0.0000
Standard deviation	0.1678	0.2432
Skewness	0.2828	0.2454
Kurtosis	9.4892	20.7567
Skewness–Kurtosis test for normality	592.70 (0.0000)	982.69 (0.0000)
ADF (5% critical value: −2.860)	−23.456	−23.374
PP (5% critical value: −2.860)	−65.119	−159.708

SREC, Solar Renewable Energy Credit; ADF, Augmented Dickey–Fuller; PP, Phillips–Perron.

5. Results and Discussion

5.1. Estimation Results

The in-sample estimation results for each of the volatility models are presented in Tables 3 and 4 for both time series. As is evident from the results, the estimated coefficients of all individual models were similar, both in terms of scale and statistical significance. In general, SREC prices show

slightly higher degrees of persistence than electricity prices. This was reflected in β values closer to 1, significant at the 1% level. Inverse leverage effect was present for electricity prices, reflected by negative and significant γ values. This suggests that positive shocks to prices have a greater impact on the variance than negative shocks. This finding is consistent with those of [29,75,76]. The models were tested for white noise process in the residuals through the Ljung–Box Q test, and for the presence of heteroscedasticity through the ARCH test and Bartlett test. The results for these diagnostic tests can be found in the Appendix A (Tables A2 and A3). As this paper focuses on forecasting rather than on estimation, we did not place much emphasis on the in-sample fit of the models. Rather than limiting the best model selection to the in-sample fit, reliance on out-of-sample performance is crucial [67,77]. Furthermore, as noted by Zhang and Zhang, and Wang et al. [62,78], investors and other market players are more interested in the out-of-sample performance, because their concerns rely on the models' future performance.

5.2. Forecasting Results

Table 5 shows the loss functions for electricity prices. The best performing models were the ones with the smallest loss functions, signifying that the forecast error produced was small. In general, four points were clear: first, all the models produced similar loss functions, reaffirming the notion that all models perform similarly. Second, none of the forecast combination methods outperformed the best individual models in terms of MSE and MAE. Instead, the GJR-GARCH was the best forecasting model. Third, the QLIKE loss function favoured the combination methods, particularly CLS. This suggests the individual models were under-predicting volatility. Finally, the worst performing combination method was PCA, as it generated inferior forecasts in comparison with any individual model. All four results were robust to the out-of-sample size.

We applied the Diebold–Mariano test to the best performing models/combinations, GJR-GARCH and CLS, to assess whether their superior performance was actually statistically significant, and the results can be found in the Appendix A (Table A4).

The loss functions for SREC prices are presented in Table 6. The NGARCHK model and the BMA combination method are highlighted in bold to indicate their superior forecasting performance, as can be seen from the small loss functions. Just as with electricity prices, PCA was the combination method that consistently performed worst in terms of forecast accuracy, and this was reflected by the large loss functions.

Table 3. GARCH estimations and diagnostic tests for electricity prices. *** and ** denote significance at the 1% level and 5% level, respectively.

	ARCH(1)	GARCH(1,1)	GARCH-M	PARCH	NGARCHK	IGARCH	SAARCH	TGARCH	GJR-GARCH	APARCH	EGARCH
ω	0.0153 ***	0.0013 ***	0.0019 ***	0.0014	0.0005 ***	0.0006 ***	0.0010 ***	0.0045 ***	0.0012 ***	0.0032 **	-0.1292 ***
α	0.3443 ***	0.1192 ***	0.1416 ***	0.1199 ***		0.1429 ***	0.0897 ***	0.0335 ***	0.0432 **	0.0766 ***	0.1419 ***
β		0.8225 ***	0.7734 ***	0.8247 ***	0.9166 ***	0.8572 ***	0.8598 ***	0.9103 ***	0.8504 ***	0.8960 ***	0.9669 ***
γ							0.0089 ***	0.0811 ***	0.0876 ***	0.4723 ***	0.0736 ***
ϕ				1.9516 ***						1.2740 ***	
α_1					0.1891 ***						
α_2					-0.1332 ***						
k_0					-0.0368 **						
h_t			1.7077								
h_{t-1}			-1.8851 ***								

Table 4. GARCH estimations and diagnostic tests for SREC prices. *** and ** denote significance at the 1% level and 5% level, respectively.

	ARCH(1)	GARCH(1,1)	GARCH-M	NGARCHK	IGARCH	PARCH	SAARCH	GJR-GARCH	APARCH
ω	0.0138 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 **	0.0000 ***	0.0000 ***
α	1.6326 ***	0.0758 ***	0.0763 ***		0.0507 ***	0.0700 ***	0.0792 ***	0.0958 ***	0.0655 ***
β		0.9419 ***	0.9420 ***	0.9503 ***	0.9494 ***	0.9389 ***	0.9387 ***	0.9439 ***	0.9429 ***
γ							0.0024 ***	-0.0523 ***	-0.1846 ***
ϕ						2.228 ***			2.0719 ***
α_1				0.3210 ***					
α_2				-0.2585 ***					
k_0				-0.0106 ***					
h_t			2.5861 ***						
h_{t-1}			-2.5383 ***						

Table 5. Electricity log returns forecast loss functions. Best performing models/combinations in bold. Combinations in italics.

Model	MSE	MAE	QLIKE
AR(1)	0.00740	0.03268	15.82333
ARCH	0.00610	0.03005	−2.58865
GARCH	0.00543	0.02908	−2.71999
GARCH-M	0.00548	0.02867	−2.72530
PARCH	0.00544	0.02907	−2.71965
NGARCHK	0.00558	0.02921	−2.69208
IGARCH	0.00542	0.03134	−2.72385
SAARCH	0.00542	0.02884	−2.71543
TGARCH	0.00552	0.02852	−2.70458
GJR GARCH	0.00539	0.02891	−2.72011
APARCH	0.00546	0.02858	−2.71102
EGARCH	0.00554	0.02847	−2.70711
<i>Simple</i>	0.00545	0.02898	−2.72637
<i>Geometric</i>	0.00547	0.02878	−2.72292
CLS	0.00546	0.02992	−2.72772
PCA	0.00993	0.06333	−2.35884
IRMSE	0.00545	0.02898	−2.72628
BMA	0.00607	0.03745	−1.94074

CLS, Constrained Least Square; PCA, Principal Component Analysis; IRMSE, Inverse Root Mean Squared Error; BMA, Bayesian Model Averaging.

Table 6. SREC prices forecast loss functions. Best performing models/combinations in bold. Combinations in italics.

Model	MSE	MAE	QLIKE
AR(1)	0.00199	0.01629	15.13625
ARCH	0.00242	0.02292	−3.79443
GARCH	0.00106	0.01055	−5.80241
GARCH-M	0.00105	0.01039	−5.80483
PARCH	0.00106	0.01057	−5.78668
NGARCHK	0.00099	0.00981	−5.85620
IGARCH	0.00105	0.00957	−5.78992
SAARCH	0.00106	0.01055	−5.84121
GJR GARCH	0.00105	0.01047	−5.79137
APARCH	0.00105	0.01048	−5.78757
<i>Simple</i>	0.00100	0.01113	−4.96500
<i>Geometric</i>	0.00101	0.01027	−5.73398
CLS	0.00099	0.01107	−4.74753
PCA	0.00210	0.02379	−4.44182
IRMSE	0.00101	0.01082	−5.12598
BMA	0.00099	0.00939	−5.03075

Diebold–Mariano tests were carried out to test the superior predictive ability of the two models, NGARCHK and BMA, and the results can be found in the Appendix A in Table A5.

6. Conclusions and Policy Implications

The main aim of this study was to forecast policy volatility in the solar photovoltaic market given the abrupt changes to renewable energy policy, particularly with respect to solar, in many countries in recent years. The need for improved accuracy in volatility forecasting for renewable energy technologies is evident in the increasing implementation of investment decision-making methodologies that move away from static discounted cash-flow techniques, towards non-static models that include the value of flexibility in the decision-making process, such as real options. In order to accurately evaluate a potential investment using these methodologies, a reliable estimate of the volatility of the

future cash flows is essential. We explored the importance of policy and electricity price uncertainty for renewable investment decisions in solar photovoltaic and the most accurate way to forecast both. We used Solar Renewable Energy Credits to proxy for policy uncertainty and applied our analysis to the Pennsylvania, Jersey, Maryland Power Pool (PJM) electricity and the New Jersey SREC market, the largest in the United States. We considered a number of GARCH-class models and combinations of such models to model the volatility of the two sources of uncertainty over a period of study of 11 years. By focusing on the out-of-sample forecasting performance of the models and combinations of models and through the computation of loss functions, we reached several important conclusions. First, by implementing a combination approach, we were able to obtain superior forecasts for policy and electricity price volatility compared to the majority of individual models, with results that are robust to a smaller sample range. Our findings were that individual models under-predict volatility. While several previous studies consider and forecast electricity price volatility in solar energy, this is the first study, to our knowledge, that includes both electricity price and policy volatility. We used SREC prices as a proxy for policy volatility because SREC market participants are constantly exposed to fluctuations in the prices of these certificates. Moreover, profits made from the trading of the SRECs represent one of the major sources of income for developers. Hence, we modelled policy uncertainty by analysing SREC prices.

Our study has important implications for both policymakers and investors. We have shown that there is significant volatility surrounding Solar Renewable Energy Credits, our proxy for policy (a high degree of volatility persistence, as displayed by the β parameter close to 1). We chose to analyse the New Jersey market as it has one of the most established SREC markets. Despite the rapid decline in the cost of solar photovoltaic and other renewable technologies, recent reports suggest that investment in renewable energy is slowing. Traditionally, in order to attract investment in renewable energy, policy supports are introduced to make such investment attractive and competitive with non-renewable energy sources. Consequently, a large part of the return investors receive is based on the revenue generated from these policy supports. In markets that use Solar Renewable Energy Credits, these credits provide a large incentive for solar investment. Due to the reliance on such policy supports to drive the investors return, uncertainty that these incentives will persist over the lifetime of the investment will be factored into the investors' required rate of return. Previous examples of abrupt and significant policy changes from around the world suggest that investors are absolutely correct to be concerned about policy instability. The more uncertainty that exists, the riskier the investment will be perceived to be. As a result, higher policy volatility will lead to a higher risk premium, and hence a higher cost of capital for renewable energy projects. This will lead to lower investment in such projects, slowing the move towards alternatives to fossil fuels.

Governments around the world have been unveiling incredibly ambitious strategies for combating climate change, the majority of which include plans to significantly increase the amount of energy sources from renewables. For example, Ireland plans to generate 70% of electricity from renewable sources by 2030, while Spain has targeted 100% generation from renewables by 2050. Canada plans to phase out coal by 2030 and triple renewable energy generation over the same time period, and the United Kingdom has planned to achieve a 57% reduction in greenhouse gas emissions over 1990 levels. Each of these countries has also unveiled a series of policies to assist in achieving these ambitions. What is clear is that implementing appropriate policy is essential and that the stability of policy is of considerable importance in order to attract sufficient investment to achieve these targets. For policymakers, it is clear that in order to move towards reaching CO₂ emissions reduction targets, keeping policy uncertainty to a minimum will foster further investment in solar PV by reducing perceived risk and attracting more capital at a lower required rate of return. One potential tool for policymakers to reduce policy uncertainty, in this case SREC price uncertainty, is by setting a price ceiling and a price floor in order to reduce the large volatility in SREC prices. In the state of New Jersey, there is a penalty for non-compliance with the SREC system called the Alternative Compliance Payment (ACP). The ACP sets the maximum amount of incentive receivable for the particular year, therefore acting as the upper

bound of the SREC prices: if the SREC price goes above the ACP, suppliers will simply pay the penalty price. However, there is currently no price floor in the SREC market, leaving investors exposed to downside price uncertainty. Inserting a price floor could ensure a minimum SREC inflow. For potential investors, we have identified improved forecasts for the major sources of uncertainty surrounding investment in solar PV, namely, electricity price uncertainty and policy uncertainty. This information can be combined and incorporated into real options valuation, allowing for a more accurate valuation of solar PV projects. Alternatively, investors can utilize the volatility estimate to alter the discount rate of the investment. The discount rate applicable to projects can change over time as the risks facing a firm change. Investors could express the discount rate as a function of volatility, so that in periods of high volatility, the discount rate can be increased to reflect the higher risk, and vice versa.

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Appendix A

Table A1. Out-of-sample details.

Range	01/01/07–01/01/18	01/01/14–01/01/18
Out of sample	Year 1: weight estimations	Years 2–4: loss function computation

Table A2. Models' diagnostic tests for electricity prices, Ljung–Box Q, ARCH, and Bartlett test results are reported.

Diagnostic Tests	ARCH(1)	GARCH(1,1)	GARCH-M	PARCH	NGARCHK	IGARCH	SAARCH	TGARCH	GJR-GARCH	APARCH	EGARCH
Q(20)	338.7831 [0.0000]	31.4653 [0.0493]	36.8489 [0.0122]	32.0447 [0.0428]	24.5856 [0.2177]	34.0167 [0.0260]	42.1856 [0.0026]	76.0232 [0.0000]	34.0402 [0.0259]	56.4840 [0.0000]	59.4982 [0.0000]
ARCH(20)	207.509 [0.0000]	27.540 [0.1207]	33.808 [0.0275]	28.063 [0.1079]	21.949 [0.3433]	31.296 [0.0514]	37.929 [0.0090]	71.248 [0.0000]	30.178 [0.0670]	51.964 [0.0001]	55.363 [0.0000]
B	2.9441 [0.0000]	1.7461 [0.0045]	1.5373 [0.0177]	1.7838 [0.0034]	0.9293 [0.3536]	1.5432 [0.0171]	2.1029 [0.0003]	3.3496 [0.0000]	1.7366 [0.0048]	2.7288 [0.0000]	2.8610 [0.0000]

Table A3. Models' diagnostic tests for SREC prices. Ljung–Box Q, ARCH, and Bartlett test results are reported.

Diagnostic Tests	ARCH(1)	GARCH(1,1)	GARCH-M	NGARCHK	IGARCH	PARCH	SAARCH	GJR-GARCH	APARCH
Q(20)	116.7365 [0.0000]	22.0905 [0.3356]	18.4212 [0.5597]	17.7214 [0.6058]	35.3338 [0.0184]	21.8372 [0.3494]	20.7718 [0.4107]	20.6662 [0.4170]	20.6217 [0.4197]
ARCH(20)	100.200 [0.0000]	22.125 [0.3338]	18.479 [0.5559]	17.680 [0.6084]	35.630 [0.0170]	21.895 [0.3462]	20.719 [0.4138]	20.698 [0.4151]	20.668 [0.4169]
B	1.3635 [0.0486]	1.8870 [0.0016]	1.6496 [0.0087]	0.6078 [0.8538]	2.4106 [0.0000]	1.8576 [0.0020]	1.8809 [0.0017]	1.8013 [0.0030]	1.7982 [0.0031]

Table A4. Electricity prices: Diebold–Mariano test statistic for forecast accuracy of GJR-GARCH and CLS. MSE and MAE are used as criteria (following Mohammadi and Su, [79]). In panel A, we evaluate the forecast accuracy of the GJR-GARCH compared to that of all other models; while in panel B, we evaluate the CLS combination with all other models.

Model	Criteria: MSE	Criteria: MAE
A. Benchmark: GJR-GARCH		
AR	−1.581	−5.03 ***
ARCH	−1.082	−2.134 **
GARCH	−1.608	−1.399
GARCH-M	−1.018	0.7794
PARCH	−1.571	−1.299
NGARCHK	−1.109	−1.01
IGARCH	−0.3787	−2.533 **
SAARCH	−4.256 ***	0.5236
TGARCH	−1.269	0.7777
APARCH	−1.315	0.8923
EGARCH	−1.165	0.7751
<i>Simple</i>	−0.9942	−0.5939
<i>Geometric</i>	−1.038	0.4159
<i>CLS</i>	−1.031	−1.871 *
<i>PCA</i>	−2.11 **	−8.647 ***
<i>IRMSE</i>	−0.9984	−0.6264
<i>BMA</i>	−3.378 ***	−5.075 ***
B. Benchmark: CLS		
AR	−1.605	−2.57 **
ARCH	−1.078	−0.1233
GARCH	0.7346	1.722*
GARCH-M	−0.3296	1.529
PARCH	0.6831	1.695 *
NGARCHK	−1.073	1.583
IGARCH	0.517	−3.173 ***
SAARCH	0.8164	1.791 *
TGARCH	−1.11	1.403
GJR GARCH	1.031	1.871 *
APARCH	0.2457	1.531
EGARCH	−1.077	1.347
<i>Simple</i>	0.5145	1.43
<i>Geometric</i>	−0.05019	1.468
<i>PCA</i>	−2.146 **	−9.689 ***
<i>IRMSE</i>	0.5358	1.433
<i>BMA</i>	−3.462 ***	−4.097 ***

*** Indicates significance at the 1% level, ** at 5%, and * at 10%.

Table A5. SREC prices: Diebold–Mariano test statistic for forecast accuracy of NGARCHK and BMA. MSE and MAE are used as criteria (following Mohammadi and Su, [79]). In panel A, we evaluate the forecast accuracy of the NGARCHK compared to that of all other models; while in panel B, we evaluate the BMA combination with all other models.

Model	Criteria: MSE	Criteria: MAE
A. Benchmark: NGARCHK		
AR	−3.122 ***	−3.588 ***
ARCH	−2.369 **	−15.22 ***
GARCH	−1.512	−2.106 **
GARCH-M	−1.484	−2.045 **
PARCH	−1.486	−1.873 *
IGARCH	−1.38	1.337
SAARCH	−1.539	−2.059 **
GJR GARCH	−1.331	−1.787 *
APARCH	−1.334	−1.724 **
Simple	−0.9922	−10.03 ***
Geometric	−1.11	−2.451 **
CLS	−0.1049	−4.883 ***
PCA	−2.611 ***	−4.291 ***
IRMSE	−1.146	−6.094 ***
BMA	−0.04666	0.7067
B. Benchmark: BMA		
AR	−3.178 ***	−3.493 ***
ARCH	−2.388 **	−12.93 ***
GARCH	−1.646 *	−1.294
GARCH-M	−1.645	−1.205
PARCH	−1.593	−1.25
NGARCHK	0.04666	−0.7067
IGARCH	−1.596	−0.2902
SAARCH	−1.67 *	−1.282
GJR GARCH	−1.487	−1.209
APARCH	−1.477	−1.201
Simple	−0.5043	−2.612 ***
Geometric	−1.222	−1.2
CLS	0.01375	−3.814 ***
PCA	−2.614 ***	−3.831 ***
IRMSE	−0.8751	−2.018 **

*** Indicates significance at the 1% level, ** at 5%, and * at 10%.

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