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Asset characteristics of solar renewable energy certificates: market solution to encourage environmental sustainability

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Asset characteristics of solar renewable energy certificates: market solution to encourage environmental sustainability

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The solar renewable energy certificate (SREC) or green certificate outside the USA is a renewable electricity production subsidy and an environmental financial asset created by governments' policy-makers. They are meant to be a Pigouvian market-based solution to monetize social externalities in electricity use and production investment decisions. The asset pricing characteristics of the SREC market is compared with other traditional financial assets to understand the market for environmental assets. Traders of SRECs are the creators of SRECs, the owners or developers of photovoltaic projects that sell SRECs, or buyers, electric utilities that need SRECs to meet their renewable portfolio standard requirements. This creates a thin market and potential problems for efficient price discovery, liquidity and market manipulation. The contribution of this investigation is to increase the understanding of the asset characteristics of SRECs and potentially lead to a more liquid and efficient market and a more socially beneficial allocation of capital to solar electricity production.

Keywords: SRECs; green certificates; photovoltaics; solar energy; consumption asset pricing; GARCH; renewable energy; market-based environmental regulation

JEL classifications: Q2; Q42 G12

1. Introduction

The conventional production (fossil fuels and nuclear fission) of electric power has substantial adverse social externalities, such as ground, air, water, and thermal pollution and global warming. This is due to the classic Pigouvian problem of electricity prices that are less than social marginal costs. This creates an excess demand for electricity (too much use of conventional production) and an excess supply (lack of use) of "green" electricity resources, that is, conservation and renewable energy resources (Michelfelder 1993).

Policy guidance should be analyzed by social welfare modeling that shows whether policies may be Pareto-improving or not on social welfare. Michelfelder (2014) and Chu and Sappington (2013) are two papers within a literature that is scant on social welfare modeling for understanding the impacts on social benefits versus social costs of policies that directly affect the use of green and conventional electricity resources.

Michelfelder (2014) develops a social welfare function that models the Pareto-improving impacts of Pigouvian taxes and subsidies currently used in the USA and other countries' power industries in an attempt to approach social optimality. Although beyond the scope of

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this investigation for detailed discussion, Michelfelder (2014) develops the social economic welfare theory foundation of this paper. That paper shows that the piecemeal developed patchwork of electric utility rate of return regulation combined with cap-and-trade and floor-and-trade (Pigouvian forms of taxes and subsidies) of air emissions and solar renewable energy certificates (SREC) developed in the USA and elsewhere leads to suboptimal investment in either types of electric power resources. An allowed rate of return set by regulators below or equal to the cost of utility's cost of capital will cause the utility to overinvest (social costs>social benefits) in green resources and an allowed rate of return above the cost of capital will cause the classic Averch and Johnson (1962) overinvestment in conventional resources.

This paper discusses the growing use of SRECs as a form of tax/subsidy to encourage the use of photovoltaics (PV). This investigation empirically models the price behavior of SRECs as an intangible environmental asset in an effort to understand the nature of the market for this environmental asset and, hopefully, lead to more socially responsible investment in SRECs. Lastly, a goal of this paper is also to provide an example for global consideration and lessons learned from the most mature SREC market in the world and where the most SREC price data exist, the New Jersey US market.

The USA and its state governments have been formulating and implementing policies to encourage the use of clean energy on the supply side and energy efficiency on the demand side since the mid-1970s. Such examples include the National Appliance Energy Conservation Act of 1975 that required reductions in the energy use of appliances on the demand side and on the supply side the Public Utilities Regulatory Policy Act of 1978 that created a new class of non-public utility electric generation plants meant to compete with public utility electric power generation. These plants were required to capture and use the waste steam heat from the electric power generation process (co-generation of electricity and steam). Fast-forward 40 years and now we have renewable energy portfolio standard (RPS) requirements by most states in the USA. They generally require electric utilities and other electric power load-serving entities to meet a specified percentage of the electricity that they sell to be generated from renewable energy sources, such as solar, wind and biomass, since these resources create positive externalities.

The RPSs across the USA are shown in Figure 1. Most have mandatory RPSs and a few have non-binding RPS goals. Only 15 states have no goal as of 2010. For example, New Jersey requires

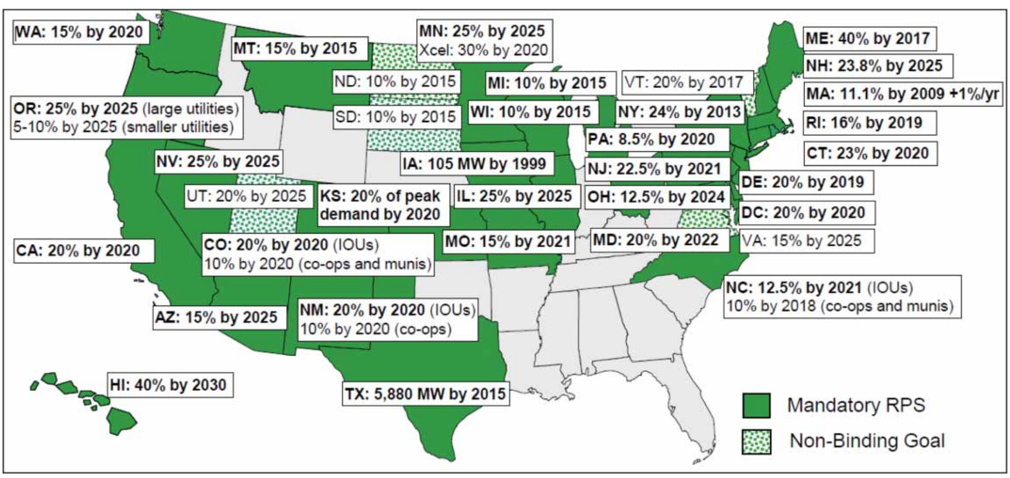

Figure 1. Renewable portfolio standards among the States.
Source: Lawrence Berkeley Laboratories (2012).

that its electric utilities meet or exceed an RPS of 22.5% by 2021. Currently, the vast majority of New Jersey's electric power (and the USA) is generated by coal, nuclear fission and natural-gas-fired plants.

Similarly in the European Union (EU), the European Parliament has established an RPS goal of 20% by 2020 with differentiated goals by country. Australia, Belgium, India, Italy, Sweden and the UK have SREC markets that trade "green certificates," as they are known outside the USA. These markets are very young at this time and are being looked to as a substitute for the poorly functioning cap-and-trade emissions markets to reduce environmental impacts. Aune, Dalen, and Hagem (2012) predict that the different mandated RPS targets across countries in the EU will not necessarily result in a cost-effective implementation of the EU target. Haas et al. (2011) compared trading green certificates with feed-in-tariffs that require electric utilities to buy back unneeded power from solar project owners at full retail rates and concluded that the economic impact of trading in green certificates is less than feed-in-tariffs.

A few states such as New Jersey and California have created SREC markets to incent households, businesses, institutions and electric utilities to invest in or sponsor solar or PV energy projects in the State. The SREC program is analogous to the US Department of Energy's cap-and-trade program of sulfuric dioxide (SO_2) and nitrous oxide (NO_X) created under various versions of the US Clean Air Act and the proposed US cap-and-trade carbon dioxide (CO_2) program that is operating in the EU. Environmental financial assets such as SO_2, NO_X and CO_2 (Europe only) pollution permits were created as market-based regulatory approaches compared to command and control methods to efficiently reduce air emissions pollution from electricity generation. The difference is that a *minimum* of solar renewable energy resource use is set by the State then electric utilities are required to either obtain the requisite level of energy from PV sources or purchase SRECs from a PV project owner to meet their requirement. Rather than cap-and-trade, SRECs are based on a "floor-and-trade" approach.

Load-serving entities such as electric utilities can either meet the requirement or pay a penalty known as the solar alternative compliance payment (SACP). The SACP must be set at a level that is greater than the difference in cost between the marginal renewable and conventional generation units to promote investment in solar projects (Felder and Loxley 2012). The SACP also imposes an obvious ceiling in the price of an SREC.

An SREC is created for each 1000 kilowatthours (kWh) of electricity produced annually by a PV project. A typical household 5 kilowatt (kW) capacity rooftop system operating at 15% capacity (in Middle Atlantic States of the USA) out of 8760 hours in a year will generate an estimated 6570 kWh (5 kW × 0.15 × 8760 hours) and therefore six SRECs per year. These SRECs are currently sold in formal SREC asset exchanges, such as the Flett Exchange, although these markets are very thin with low volumes and extremely high volatility in SREC prices and returns.

The purpose of this paper is to understand the nature of an SREC as an environmental financial asset. Most SREC transactions currently occur between the owners of the solar project that create the SRECs and the electric utility or other electric power generator to meet their requirements. That is, there are very few third party transactions in SRECs to be held in investment portfolios. Additionally, the SREC market is very thinly traded.[1] Low volumes create volatility as one substantial buy or sell order (on some days this may amount to one SREC) can cause huge jumps and declines in price. As shown in this study later, daily SREC returns can be in the hundreds of percent (positive or negative).

I use a recently developed and successfully empirically tested general consumption asset pricing model to understand the characteristics of the SREC as an environmental financial asset. This model alleviates the shortcomings of the alternative traditionally used financial models for asset valuation.

The general consumption asset pricing model is estimated with generalized autoregressive conditional heteroscedasticity (GARCH) methods for SRECs to understand and compare the asset properties of SRECs with other assets. These include returns and risk premiums levels, long-term volatilities, past and *ex ante* volatility patterns, probability distribution characteristics of prices and returns, trading volumes, intertemporal risk/return relations and whether SRECs hedge the business cycle (most assets do not). The contribution of this investigation is to increase the understanding of the asset characteristics of SRECs as an environmental financial asset. This paper presents evidence to encourage more liquid SREC markets, efficient SREC pricing, efficient allocation of capital to PV, and monetization, valuation and efficient environmental improvement in the electricity sector.

Section 2 is the review of the literature. Section 3 describes the theoretical and empirical models. Section 4 discusses the empirical results and Section 5 concludes the investigation.

2. Literature review

The literature on market-based approaches to environmental regulation is vast for cap-and-trade air pollution emissions permits. Yet, there is little but growing formal literature on SRECs in general, as SRECs are a recently adopted market-based environmental regulatory tool in the USA (Burns and Kang 2012). Burns and Kang (2012) estimate the financial value of SRECs as an incentive in all of the States that use SRECs. They use standard valuation tools such as net present value, internal rate of return, discounted cash flow and present value per Watt of electric generation capacity to estimate and compare SREC financial incentives in each state. Hart (2010) discusses the state policies and institutional systems that create SRECs in New Jersey. There is no literature that this investigation has found on the characteristics of SRECs as a financial asset for third-party investors.

Felder and Loxley (2012) find that since solar electric generation is fixed by RPSs (but increase annually) and does not depend on SREC prices, SRECs have a vertical demand curve and prices are unnecessarily volatile as a result. They suggest that a policy for creating a downward sloping demand curve needs to be implemented by making the life of SRECs dependent on market conditions. Figure 2 shows the vertical demand curve for SRECs obtained from Felder and Loxley (2012). The demand curve is fixed and vertical at the annual SREC requirement with the ceiling price set at the SACP. Small changes in supply along the vertical demand curve can cause large changes in price.

Borenstein (2012) discusses that Pigouvian taxes on externalities are the best method to internalize emission pollution from electricity generation and therefore tradable emissions permits or

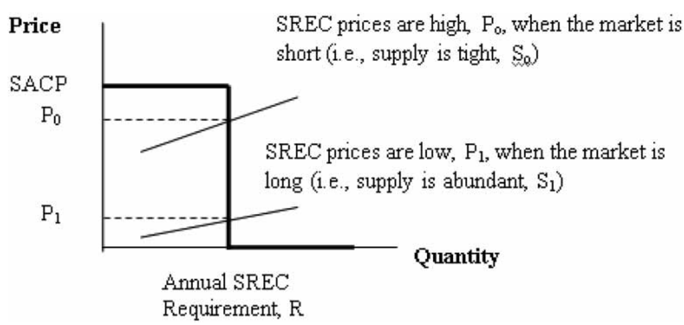

Figure 2. SREC demand and supply conditions.
Source: Felder and Loxley (2012).

other forms of tax on externalities should be adopted to encourage investment in renewable energy. Pigouvian taxes and subsidies increase or decrease the private marginal cost curve, respectively. Tradable emissions permits have been not been widely supported by state governments in the USA, but they are rapidly developing policies that create renewable energy requirements and incentives and taxes as a substitute in the form of SRECs. Borenstein (2012) views the RPS mandates and minimum shares of electric power of retail electric suppliers that must come from renewables combined with tradable credits as a form of tax or subsidy (depending on whether the utility is paying for or receiving payment from credits) for electric generation pollution abatement by renewable energy. SRECs are one such form of credit.

Emissions permits, as currently structured, do not seem to be working well as a Pigouvian tax or subsidy. Muller, Mendelsohn, and Nordhaus (2011) find that the marginal damage from SO_2 emissions from coal plants exceeds the marginal cost of abatement, as reflected by the market price of emissions. Muller, Mendelsohn, and Nordhaus (2011) also show that the gross external environmental damage (GEED) from coal plants has a GEED equal to \$0.028 per kWh excluding CO_2 GEED or \$0.036 per kWh including CO_2. Since an SREC price at a low value of \$100 reflects \$0.10 per kWh, it seems that SREC prices are substantially higher than the GEED of coal plants. Pigouvian taxes and subsidies increase or decrease the private marginal cost curve, respectively, to reflect social marginal cost. Although it is beyond the scope of this study to analyze the efficient price for these environmental financial assets, policy instruments that affect emissions permits and SREC prices need to be evaluated to more closely reflect the marginal damage costs of conventional electric power generation.

3. Model

The literature on financial asset pricing models, such as the capital asset pricing model (CAPM) and the consumption asset pricing model applied herein, is vast so for the sake of brevity, I briefly discuss some literature that summarizes the vast amount of work leading to the model used in this paper and the summary of shortcomings leading to the general indictment of the CAPM and why it is not the foundation asset pricing model in this paper.

The main financial model used for the analysis of SRECs is the generalized consumption asset pricing model. The model has been recently derived, developed and empirically tested in Michelfelder and Pilotte (2011) and Cochrane (2004) and further applied and tested for public utility stocks, the cost of capital and US equities markets in Ahern, Hanley, and Michelfelder (2011). There are many increasingly restrictive variants of the model that led to this generalized version that are discussed and cited in Michelfelder and Pilotte (2011) and used as foundations to develop the model in that article. Models such as the CAPM, the intertemporal CAPM of Merton (1973), the intertemporal asset pricing model of Campbell (1993), and the habit-persistence model of Campbell and Cochrane (1999), as a partial list, are special cases of the model used in this paper. The summary of the literature on the CAPM, its many shortcomings and the concluding recommendation to not use the CAPM are found in Fama and French (2004).

Some highlights of the general consumption asset pricing model are that it makes no assumptions about the efficiency of the asset market. There are no constraints on the investor's degree of risk aversion or limits on the coefficient of risk aversion. The model prices the risk actually faced by the investor (not systematic risk only as with the CAPM) and does not assume the investor has a perfectly diversified portfolio that eliminates all unique risk of an asset (also a CAPM assumption). The model does not even require that there is a positive relation between return and risk as other asset pricing models do. This property will be discussed below. Since the SREC market is thinly traded, the CAPM would understate beta, the CAPM measure of risk since SREC prices would not respond to changes in market prices as the SRECs trading volume is thin and prices not sensitive to stock market trading volumes. A thinly traded asset does not affect the ability of the model to estimate the *ex ante* risk premium but thin trading will exacerbate the volatility of an asset's return and its expected value that cannot be expected to continue if the market volume and liquidity grows over time. This issue will be considered in the empirical analysis.

Consistent with Michelfelder and Pilotte (2011) and Ahern, Hanley, and Michelfelder (2011), the model is specified as the *ex ante* risk premium of an asset *i* as a function of the volatility of the asset's *ex ante* return:[2]

$$E_t[R_{i,t+1}] - R_{f,t} = -\frac{\mathrm{vol}_t[M_{t+1}]}{E_t[M_{t+1}]}\mathrm{vol}_t[R_{i,t+1}]\,\mathrm{corr}_t[M_{t+1}, R_{i,t+1}], \tag{1}$$

where $R_{i,t+1}$, is the *ex ante* return on asset *i*, $R_{f,t}$, the risk-free rate of return in time *t*, M_{t+1}, the stochastic discount factor (SDF), vol_t, the volatility of the variable conditioned on information available in time *t* and corr_t, the conditional correlation.

The SDF is also the intertemporal marginal rate of substitution in consumption:

$$M_{t+1} = \left(\frac{1}{1+k}\right)\frac{U_{c,t+1}}{U_{c,t}}, \tag{2}$$

where the U_c's are the marginal utilities of consumption in the next period, $t+1$, and the current period, *t*, and *k* is the discount rate for period *t* to $t+1$. The ratio of the marginal utilities of consumption for two time periods, $U_{c,t+1}/U_{c,t}$, rises if the future dollar value of future consumption falls. The marginal utility of the future consumption rises as future consumption declines below current consumption. Referring to Figure 3, a concave utility function of consumption for the investor has a higher slope as you move left from a higher consumption level, say \$8000 in consumption on Figure 3 to a lower consumption level such as \$4000. This property is what generates the ability of the model to identify business cycle (as represented by consumption expenditures) hedging properties of an asset.

The ratio, $\mathrm{vol}_t\,[M_{t+1}]/E_t\,[M_{t+1}]$, is the slope of the mean–variance frontier. Intuitively, this slope reflects the volatility of utility from intertemporal consumption relative to expected utility. If volatility rises, investors require a greater risk premium as compensation. I initially

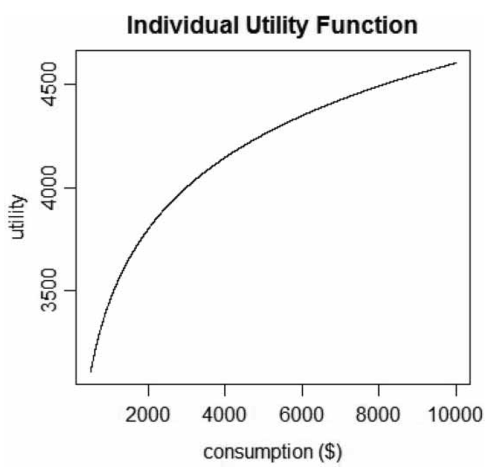

Figure 3. Investor's Concave utility function.

assume that this slope and the correlation between each asset's return and the SDF are stable over time, but also analyze the stability of the slope. The sign (+ or −) of the relation between the expected risk premium and the conditional volatility of an asset's expected risk premium is determined by the conditional correlation between the asset's *ex ante* return and the SDF or corr_t. The sign of the relation between the expected risk premium of an asset and the conditional volatility of that asset's risk premium is the opposite sign of the correlation of the asset return and the ratio of intertemporal marginal utilities in consumption. That is, when the correlation is positive, the asset will have a negative relation with its risk. When the correlation is equal to negative one, the conditional expected risk premium is perfectly positively correlated with its conditional volatility. A positive relation between the conditional expected risk premium and conditional volatility occurs if $-1 < \text{corr}_t < 0$. A negative relation occurs if $0 < \text{corr}_t < 1$. For an asset that represents a perfect hedge against shocks to the marginal utility of consumption over time, $\text{corr}_t = 1$ and there will be a perfect negative correlation between the conditionally expected risk premium and its volatility.

Viewing a decline in consumption as a contraction in the business cycle, and assuming a concave utility function (as a function of consumption) for the investor, a reduction in next period consumption increases marginal utility as the investor moves left on the utility function. The hedging asset generates positive changes in returns when the business cycle is moving into a contraction, and therefore the asset is a business cycle hedge. Therefore, if the empirically estimated coefficient on the return/risk relation is negative, the asset is a business cycle (consumption) hedge. Additionally, it is possible to have higher risk associated with a return less than the risk-free rate. This means that it is conceivable that an investor may be willing to pay for a specific *pattern* of higher volatility that an asset has that delivers rising returns when she needs it most – during a business cycle downturn. A hedging asset pays more in bad times and less in good times, and therefore plays the role of insurance, paying to avoid hardship. It is not obvious *a priori* whether SRECs should be a business cycle hedge.

An obvious way to estimate Equation (1), the relation between risk and return is a simple GARCH-in-Mean model (GARCH-M) of conditional variance. The GARCH-M model was developed specifically for estimating asset returns mean and volatility relations. I use GARCH-M since it specifies the conditional expected risk premium as a linear function of its conditional volatility, which is the specification of Equation (1). There is a vast body of literature that estimates asset pricing models with the GARCH and GARCH-M methods and therefore we will not attempt to summarize them here. The GARCH-M model was initially developed and tested by Engle, Lilien, and Robins (1987) to estimate the relationship between US Treasury and corporate bond risk premiums and their expected volatilities. The GARCH-M model that I use is specified as

$$R_{i,t+1} - R_{f,t} = \alpha_{i,t}\sigma^2_{i,t+1} + \varepsilon_{i,t+1}, \tag{3}$$

$$\sigma^2_{i,t+1} = \beta_0 + \beta_1\sigma^2_{i,t} + \beta_2\varepsilon^2_{i,t} + \eta_{i,t+1}, \tag{4}$$

$$\varepsilon_{i,t}|\psi_{t-1} \sim \text{GED}(0, \sigma^2_{i,t}, k), \tag{5}$$

where $Ri,_{t+1}$, is the expected total return on asset i, $R_{f,t+1}$, the risk-free rate of return, $\sigma^2{}_{i,t+1}$, the conditional or predicted variance of the risk premium that is conditioned on past information (ψ_{t-1}), $\varepsilon_{i,t}$, $\eta_{i,t+1}$, the error terms, and $\varepsilon_{i,t}$ distribution is specified with the general error distribution (GED) and is conditional on ψ_{t-1} and k, the kurtosis parameter for the GED.

The conditional distribution of the error term is specified as the GED to accommodate leptokurtosis (thick tails) found in the risk premium data.

The parameter, $\alpha_{i,t}$ that I refer to below as "alpha" is the return-to-risk coefficient as specified in Equation (1) and shown empirically in Equation (2) as

$$\alpha_{i,t} = -\frac{\mathrm{vol}_t[M_{t+1}]}{E_t[M_{t+1}]}\mathrm{corr}_t[M_{t+1}, R_{i,t+1}]. \tag{6}$$

This parameter represents the relation between risk premium and risk and the algebraic sign of this parameter indicates whether the asset is a business cycle hedge. The parameter is a function of conditional variance and is time varying as the conditional standard deviation of the return is included in the conditional correlation, $\mathrm{corr}_t[M_{t+1}, R_{i,\ t+1}]$, of the SDF and the return, hence the time subscript on the coefficient. As stated above, if $\mathrm{corr}_t[M_{t+1}, R_{i,t+1}]$ is positive, then alpha is negative and the asset is a hedge as the return rises when marginal of consumption rises due to a drop in aggregate consumption. Since the theoretical model, Equation (1), is specified without an intercept, I will estimate the model without the intercept, but test the model with intercepts. The intercept should intuitively be zero as otherwise would indicate evidence of an excess return premium, i.e. one not associated with risk. The intercept in Equation (2) is restricted to zero, as specified by the general asset pricing model. The "no-intercept" specification has been found to be robust in producing consistently positive and significant relationships between common stock risk premiums and risk in GARCH-M models. These findings are discussed in Lanne and Saikkonen (2006) and Lanne and Luoto (2007). Maximum likelihood estimation is used to estimate the GARCH-M model. The data and empirical analysis are discussed next.

4. Results

This investigation models the asset characteristics of the New Jersey US SREC market, the most mature SREC market globally (and has the most price data) and compares it with traditional asset markets such as the US stock market, US corporate bonds and the US gold spot market. The purpose is to compare the market characteristics of SRECs with stocks, bonds and gold. Although there are other SREC markets, such as California, Massachusetts, Delaware, the EU and a few members, and other countries across the globe, the New Jersey market is the most developed market, the oldest market and second in size only to California (Burns and Kang 2012). The New Jersey SREC price and trading volume data come from the New Jersey Office of Clean Energy SREC website. That database, which is publicly available, contains daily transactions as reported by registered SREC account holders in the State. The data include the transactions revenues for the day and the volume traded, so the average daily price is obtained by dividing revenues by volume. The data begin on 18 August 2004 and end on 31 December 2011. Trades did not occur every business day, especially in the early years so returns are calculated by the change in price relative to the most recently reported transactions day. Sometimes trades are reported on holidays and weekends. An inspection of the data shows that there are days with a trading volume of one SREC and returns in the hundreds of percent on that day based on the sale of one SREC, therefore the issue of thin trading and associated volatility will be addressed. The mean daily trading volume was 869 from 2004 to 2011 with a maximum daily volume of 93,301 and a minimum of 1.

The US stock market data are the University of Chicago's Center for Research in Security Prices (CRSP) Fama-French daily returns based on the CRSP value-weighted US stock market index that includes most stocks on the NYSE, NASDAQ and AMEX and includes approximately

11,000 stocks. This data are publicly available and obtained from Professor Kenneth French's data website French 2012). The US Corporate Bonds daily returns data are the relative daily change in the Bank of America Merrill Lynch US Corporate Master Bond Total Return Index. This index represents the return performance of US investment-grade rated corporate debt (based on Fitch, Moody's and S&P bond ratings) publicly traded in the US bonds market. The source of the data is the Bank of America Merrill Lynch and the data are available publicly from the Federal Reserve of St. Louis (2012) Economic Database, known as FRED®.

Daily gold returns are the change in price relative to the previous day. The gold price is the daily US dollar price per troy ounce in New York. The risk-free rate of return is the daily return on the one month US Treasury Bill from the Fama-French database French 2012). All returns observations range from 1 September 2004 to 31 December 2011. The existence of the New Jersey SREC market and data (recall that it is the oldest market for SRECs) starts at 18 August 2004 and therefore determined the timeframe of the analysis.

Table 1 presents the descriptive statistics for SREC, the US stock market, US corporate bonds and gold risk premiums. All returns are daily total returns minus the risk-free rate of return. I added a variable denoted as "LogSREC," which is the natural log of (1 + SREC total return), or the continuous return, minus the risk-free rate. Since SRECs are thinly traded, especially during the early years starting in 2004, the range of daily returns is extreme and skewed with the range during the time period from −66.9% to 505.6%. Therefore I obtained log returns to minimize the effects of extreme skewness on the distribution of returns and regression estimations and residuals. I continue to report non-transformed SREC returns data for comparison.

The means and standard deviations show that stocks have the most relative risk as measured by the coefficient of variation, the ratio of standard deviation to the mean. LogSREC has the second highest relative risk although LogSREC mean returns and standard deviation are almost 20 times larger than stocks. All returns except for LogSREC have the same order of magnitude and range from 0.0132% to 0.0695%. The LogSREC daily mean risk premium is 0.4293% which compounds to a 192% annual return assuming 250 trading days.

The Jarque-Bera (JB) statistics, a goodness-of-fit test of the departure of the distribution of a data series from the normal, reject normality at the 0.01 level for each asset's risk premium series. The skewness and kurtosis parameters of the risk premiums indicate that the rejection of normality is due mainly to excess kurtosis (thick tails) rather than asymmetry (skewness) relative to the normal distribution, except for SREC that has high positive skewness and thick tails. Stocks, bonds and gold have slightly negatively skewed risk premiums, meaning that they had a greater tendency to be negative during the timeframe. This is most likely due to the time frame of 2004–2012 that included the financial markets crises that began in 2008. Skewness should be equal to 0 for symmetry and excess kurtosis equals 0 if thick/thin tails not peakness in the distribution exists as characteristic of the normal. The generalized error distribution (GED) is used in the regressions to accommodate thick tails in the risk premiums and residuals. Accommodating excess kurtosis in the data improves the efficiency of the regression estimates. If skewness was a problem, the skewed version of the GED (SGED) could be used to accommodate asymmetry. According to McDonald, Michelfelder, and Theodossiou (2009), if significant skewness exists, the estimated intercept will be biased if one is specified in the model. McDonald, Michelfelder, and Theodossiou (2010) test the GED, SGED and many other symmetric and asymmetric distributions that also address kurtosis in the financial model estimation.[3]

I report the 1st, 3rd and 12th autocorrelations (ARs) for squared risk premiums. These are proxies for variance based on the assumption of zero expected value. The ARs for all assets except SREC show evidence of variance AR and are statistically significant. The Q(1, 3, 12 AR lag) statistics reject the null hypothesis of no AR in the variance of the risk premiums in the first lag, first 3 lags and first 12 lags at the 0.01 level for all assets except SRECs. Reported

Table 1. Descriptive statistics for asset risk premiums.

Daily risk premium $(R_{\tau,t+1}-R_{f,t})$							Variance of risk premium $(R_{\tau,t+1}-R_{f,t})^2$		
Asset type	Mean (× 100)	Std. dev. (× 100)	Coeff.Var. (SD/mean)	Skewness	Kurtosis	JB	ρ_1	ρ_3	ρ_{12}
SREC[a]	3.5511	29.7816	8.39	4.92	62.57	234,093.6***	0.01	0.01	0.00
LogSREC[a]	0.4293	24.0086	55.92	0.36	9.15	2468.0***	0.30***	0.07***	0.04***
US stocks	0.0221	1.4476	65.50	−0.15	11.47	5531.9***	0.20***	0.24***	0.10***
Corp. bonds	0.0132	0.3492	26.45	−0.33	5.72	605.0***	0.19***	0.10***	0.11***
Gold	0.0695	1.3010	18.72	−0.08	7.96	1899.7***	0.16***	0.21***	0.21***

Notes: The time series time frame is from 1 September 2004 to 31 December 2011 with approximately 1848 daily observations. Observations slightly differ across assets due to a few differences in trading days. The JB statistic is a goodness-of-fit test of the departure of the distribution from the normal that uses the levels of excess kurtosis and skewness of a variable as inputs. The JB statistic is χ^2 distributed with 2 degrees of freedom. The variance AR coefficient is ρ_t, where t is the lag length in months.
[a]The minimum and maximum range for SREC daily risk premiums before "trimming" the skewness and extreme values of the distribution with natural log transformation of (1+return) to get continuous returns were 505.6% and −66.9%, respectively. The extreme values are due to thin trading.
*Significance for the JB or Q(1, 3, 12 lags) tests for AR at the 0.10 level for a one-tailed test.
**Significance for the JB or Q(1, 3, 12 lags) tests for AR at the 0.05 level for a one-tailed test.
***Significance for the JB or Q(1, 3, 12 lags) tests for AR at the 0.01 level for a one-tailed test.

ARs indicate that these rejections are due to positive ARs. This indicates that substantial positive AR in squared risk premiums exists as well as suggests that autoregressive conditional heteroscedasticity (ARCH) is present in the assets' risk premiums series. The existence of ARCH effects in the risk premium series may adversely affect the efficiency of the regression estimates of the model. This is one of a number of reasons why I use GARCH methods to estimate the consumption asset pricing model.

Table 2 presents the correlation matrix for the total returns of the assets. LogSREC is an excellent asset candidate to diversify the risk of stocks, bonds and gold due to its negative and low correlation with other returns. Not surprisingly, corporate bonds and gold are strong stock market hedges with statistically significant negative correlations of −0.29 and −0.10, respectively. The property of SRECs as stock, bond and gold market hedges as well as a socially responsible asset should be attractive to portfolio managers.

The kurtosis values given in Table 1 and the JB statistics show that returns are not normally distributed due to thick tails or leptokurtosis and therefore I estimate the GARCH-M system specifying the conditional distribution for the error term with the GED. This specification will increase the efficiency of the estimates compared with the normal distribution. The GED is less restrictive than the normal as it accommodates thick tails and it nests the normal and t distributions.

Table 3 presents the GARCH-M results for all assets. The GED parameter k differs significantly from the normal distribution value of $k = 2$ with p levels at or lower than 0.05. Lagrange Multiplier ARCH statistics indicate that the model is effective at removing most of the ARCH effects from the regression residuals, except for stocks and bonds, where significant ARCH effects in the residuals remain. The sum of the coefficients in the variance equation, $\beta_1 + \beta_2$, is close to one or greater in every variance equation. A sum of one is evidence of the existence of an integrated GARCH process, as discussed by Engle and Bollerslev (1986), whereby returns shocks have a permanent effect on the conditional variance and the asset's value.

The slopes on conditional variance, or alphas, in the mean equations are all positive. They are significant at p values equal or less than 0.01 for all assets except SREC. The GARCH-M specification of conditional variance provides evidence that there is a long-term positive relation between risk and return, and that none of the assets are business cycle consumption hedges. LogSREC, however, has a low alpha of 0.047 and therefore its returns are not highly correlated with business cycles and therefore may be a relatively good business cycle hedge.

I included the intercept for the LogSREC model and also in the SREC model for comparison since the alpha was statistically significant only with its inclusion in the model. The alpha for the SREC model is insignificant with either specification.

Table 2. Correlation matrix of asset total returns.

Asset	SREC	LogSREC	US stocks (CRSP value-weighted index)	US corp. bonds	Gold
SREC	1.00				
LogSREC		1.00			
US stocks	−0.04*	−0.05	1.00		
US corp. bonds	0.00	0.01	−0.29***	1.00	
Gold	−0.00	−0.01	−0.08***	0.07***	1.00

Notes: The results are correlation coefficients of the daily returns among the assets as shown in Table 3. The time series frame is from 1 September 2004 to 31 December 2011 with 1848 daily observations. The number of observations differs across assets due to differences in the number of trading days, especially SREC trading days early in the existence of SRECs. The daily observations of returns across assets have consistent trading dates, therefore some observations in each asset class have been deleted to obtain consistency for correlations.

Table 3. GARCH-M estimation of risk-return asset relations.

Mean equation			Variance equation			GED parameter (k) ($k = 2$ for normality)	LM-ARCH	Log-L
Asset	Constant	$\sigma^2_{i,t+1}$	Constant	$\varepsilon^2_{i,t}$	$\sigma^2_{i,t}$			
SREC (×100)[a]	0.016 (0.048)	0.004 (0.344)	0.014*** (0.002)	1.657*** (0.0.300)	0.146*** (0.037)	0.570*** (0.020)	0.14	567.1
LogSREC	−0.002** (0.001)	0.047*** (0.020)	0.015*** (0.002)	1.187*** (0.104)	0.191*** (0.041)	0.596*** (0.022)	0.94	603.5
US stocks		4.7794*** (1.3993)	0.000*** (0.000)	0.0865*** (0.0135)	0.907*** (0.0143)	1.379*** (0.060)	2.37***	5808.0
US corp. bonds		14.209** (6.504)	0.000* (0.000)	0.436*** (0.077)	0.952*** (0.086)	1.713*** (0.075)	3.01***	8009.2
Gold		4.248*** (1.644)	0.000** (0.000)	0.0508*** (0.0105)	0.943*** (0.012)	1.448*** (0.060)	0.50	5624.7

Notes: The results above are the GARCH-M regressions for the daily risk premium on the asset ($R_{i,t+1}-R_{f,t}$) with conditional variance in the mean equation. The estimated model is

$$R_{i,t+1} - R_{f,t} = \alpha_{i,t}\sigma^2_{i,t+1} + \varepsilon_{i,t+1} \text{ where } \alpha_{i,t} = -\frac{\text{vol}_t[M_{t+1}]}{E_t[M_{t+1}]}\text{corr}_t[M_{t+1}, R_{i,t+1}],$$

$$\sigma^2_{i,t+1} = \beta_0 + \beta_1\sigma^2_{i,t} + \beta_2\varepsilon^2_{i,t} + \eta_{i,t+1}.$$

The data range from 1 September 2004 to 31 December 2011 with 1848 daily observations. The number of observations slightly differs across assets due to a few differences in trading days. The conditional distribution for the error term is the GED to address non-normally distributed errors, where the GED parameter (k) is the kurtosis parameter. The GED nests the normal distribution and becomes the normal if $k = 2$. Engle's Lagrange Multiplier ARCH statistic (LM-ARCH) is a test for ARCH effects in the residuals for 12 lags. It is χ^2 distributed with 12 degrees of freedom where the degrees of freedom are driven by the number of lags tested. Log-L is the value of the log of the likelihood function. The AR(1) coefficient is the first-order autoregressive coefficient for the fitted values of $\sigma^2_{i,t+1}$. Standard errors are in parentheses.
[a]The SREC coefficients for the mean equation are multiplied by 100 due to their small values.
*p-Values equal to less than 0.10 level with two-tailed tests for regression and GED parameters, one-tailed test for LM-ARCH.
**p-Values equal to less than 0.05 level with two-tailed tests for regression and GED parameters, one-tailed test for LM-ARCH.
***p-Values equal to less than 0.01 level with two-tailed tests for regression and GED parameters, one-tailed test for LM-ARCH.

Engle, Lilien, and Robins (1987) develop the ARCH-M model and use it to estimate the relation between the conditional mean and conditional standard deviation of monthly excess holding period returns on two-month Treasury bills and 20-year AAA rated corporate bonds. They find positive coefficient and significant estimates on volatility for both return series. Campbell (1987) estimates the conditional mean and conditional variance of various Treasury bills and a portfolio of Treasury bonds, where both moments are modeled as functions of financial conditioning variables. Campbell reports large positive correlations between the fitted moments for bills and a low 0.029 for the long-term bond portfolio. The two studies are consistent in reporting a strong positive relation between risk and return for short-term bonds and a weak positive relation for long-term bonds.

There are many studies that estimate the relation between the conditional mean and conditional volatility of stock market returns. Unlike bonds, stock market results are very sensitive to changes in the methodology used to estimate the conditional volatility.

Stock returns studies such as Campbell (1987), French, Schwert, and Stambaugh (1987), Glosten, Jaganathan, and Runkle (1993), Whitelaw (1994) and Harvey (2001) show that results are sensitive to whether the conditional variance is modeled using only financial conditioning variables, a simple GARCH-M model, a GARCH-M model that incorporates financial conditioning variables in the estimation of the conditional variance, or GARCH-M models that allows positive and negative shocks to returns to have different impacts on the conditional variance.

4.1. *Robustness tests*

I perform robustness tests with the inclusion of intercept, the specification of conditional volatility and the specification of the approximating distribution of residuals as GED versus normality. The LogSREC estimation is not robust to exclusion of the intercept. Although not reported, all chi-squared tests with one degree of freedom of the log-likelihoods of the GED versus normal are rejected at p values of 0.01, which means that the GED provides a better fit of the data. All of the model estimations are robust to changes in specifications in the conditional volatility (standard deviation and log(variance)).

One concern is the intertemporal stability of the alphas. The alpha in the model is a function of conditional variance and is time varying as the conditional standard deviation of the return is included in the conditional correlation of the SDF and the return. Although the alphas are treated as constants (i.e. allowing only the conditional variance of returns to be state dependent), I investigate their time variation and stability of the hedging property of the assets over time by estimating and reviewing rolling estimates of alpha. Figure 4 plots the alphas for 500 trading day

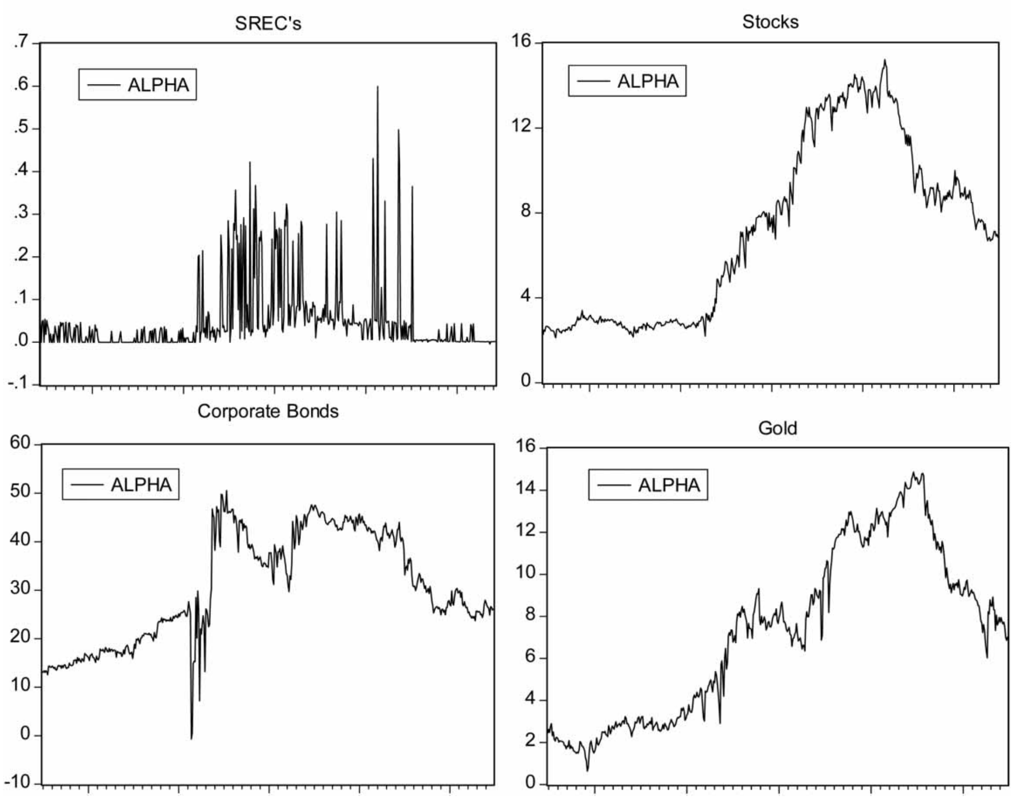

Figure 4. Rolling 2-year asset alphas (slope on $\sigma^2_{i,t+1}$) for 2006–2011.

(2 years) rolling regressions of the model estimated with GARCH-M in the same manner as described earlier. A 2-year period was used to trade off timeliness with sufficient observation of up and down stock market regimes. Whitelaw (1994) used a similar timeframe of 17 months to review of intertemporal stability of the correlation between the conditional expected values of stock market risk premiums and their conditional volatilities. The results for all assets except LogSREC are similar. Although the alpha values vary substantially over time for stocks, bonds and gold, none of them are negative. Therefore stocks, bonds and gold were not business cycle hedges either temporarily or in the long run from 2004 to the end of 2011. LogSREC alphas show that alpha has a tendency to hover near zero although it remains positive and is subject to large upward and downward spikes. This shows that the SREC asset does not have a tendency to generate returns that are correlated with the business cycle.

5. Conclusion

Globally, SRECs are becoming the focal point of market-based solutions to reduce pollution externalities associated electricity production and consumption. Although SREC policies combined with public utility rate of return regulation and emissions cap-and-trade will always result in some form of energy resource investment suboptimality based on Michelfelder (2014), the behavior of SREC prices are modeled as an environmental asset to understand the nature of the market and what changes should be considered to make the SREC market stable and attractive to capital investment. The modeling, comparison and analyses of SREC assets with stocks, bonds and gold show that SRECs are (1) extremely volatile and thinly traded, (2) are stock, bond and gold market hedges and therefore an attractive asset to add to a financial portfolio for diversification, especially one with a social responsibility investment charter and (3) although not a business cycle hedge in the USA similarly with stocks, bonds and gold, SREC returns have very low correlation with business cycles. The intertemporal nature of the return–risk relation for SRECs is not necessarily stable in magnitude but is positive in algebraic sign and hovers near zero and therefore consistently does not hedge or exacerbate returns during phases of the business cycles. A positive, rather than negative, risk–return relation indicates that SRECs are not a hedging asset as that concept is defined in consumption-based models of intertemporal choice.

The empirical results and conclusions are driven by the thinly traded market and extreme volatilities. The results are also impacted by the lumpiness of SREC deliveries to the market. This is why SREC prices in New Jersey are very low (discussed in the following) as commercial project SRECs are being dumped onto the market (victim of its own success). Therefore, the conclusions remain tentative yet these results reflect the experience of SREC pricing in the market to date.

One key policy change that would substantially improve the liquidity and stability of the SREC market development and increased market participation in solar projects is to homogenize the specifications of SRECs nationally for a country and for the EU. That would create a thicker national market rather than segmented and disjointed state markets that are currently in the USA and disjointed across member countries within the EU. One final point about market size is that the small, segmented SREC markets are highly susceptible to market manipulation.

SRECs, as a market-based environmental regulatory mechanism that is a Pigouvian tax or subsidy on electricity generation externalities similar to cap-and-trade SO_2 and NO_X emissions permits in the USA and CO_2 permits in Europe, are becoming more popular in the USA, the EU and elsewhere and the trading volume is rising, unlike SO_2, NO_X and CO_2 permits. SREC prices in New Jersey have been depressed recently. Prices ranged between \$500 and \$700 for the period 12/2008 to 6/2011 and by 12/2011 were down to \$280. By 11/2013 prices were down to \$180. This is due to a glut of large commercial project SRECs entering the market rather than a lack of interest as with emission permits.[4]

This paper suggests that it behooves portfolio managers to watch SREC asset behavior and consider adding SRECs to their portfolio to meet social responsibility goals and a more efficient financial portfolio, that is, one that generates higher returns and less risk. The problem is that there are not enough SRECs. Should they become a popular investment consideration, their prices will rise substantially which is good for short-run solar project development but maybe too quick to consider SRECs a stable asset.

More importantly, it behooves national (and EU) policy-makers to integrate the state (EU member) markets into one large market to reduce volatility of the market, increase liquidity in the market and alleviate potential market manipulation, all of which lead to a more stable market, lower risk and increase the development of solar projects.

The form of socially optimal public utility regulation combined with SRECs and RPSs is beyond the scope of this study. Further research could develop microeconomic models of the regulated firm that specify SREC-type market-based environmental regulation and rate-of-return regulation to understand how electric utilities respond to such innovative environmental regulation, similar to that of Michelfelder (2014), which is currently an underdeveloped literature.

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Notes

1. The current state centric segmentation of SREC markets is also a substantial yet partial cause of the thin markets in New Jersey and other states. Integration into one national market would expand market liquidity and reduce volatility of SREC asset prices. However, in a very recent investigation, Fell and Linn (2013) show that differences in generation mix, electricity prices and other factors can vary the value and cost effectiveness of wind and solar across location and technology. This creates major structural impediments to an integrated market for renewable energy policy instruments such as SRECs.
2. Note that the slope on conditional volatility of the return, the independent variable, is an inverse function of the conditional volatility of return itself as the conditional correlation includes the volatility in the denominator. As discussed later, this slope is very rich and complex in structure.
3. Although it may seem intuitive to specify the approximating distribution of the regression errors with the less restrictive SGED rather than the GED since the SGED also accommodates asymmetry, the SGED has an additional parameter to estimate, the skewness parameter. Over-parameterizing a distribution reduces the efficiency of the estimates since it requires the estimation of another parameter. See the Appendix for more characteristics of the GED distribution.
4. See the State of New Jersey Office of Clean Energy website.

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*Working papers by Felder and Loxley (2012) and Michelfelder (2014) are from the authors at ffelder@rutgers.edu and richmich@rutgers.edu, respectively.

Appendix. The generalized error distribution and nested distributions

The GED and two of its nested distributions, the Student's t and normal, are:

$$\mathrm{GED}(\varepsilon, \beta, \sigma, k) = \frac{C}{\sigma}\exp\left[-\frac{1}{\theta^k \sigma^k}|\varepsilon|^k\right],$$

$$t(\varepsilon, \beta, \sigma, n) = \frac{C}{\sigma}\left[1 + \frac{1}{((n+1)/2)\theta^2\sigma^2}|\varepsilon|^2\right]^{-(n+1/2)} \text{ and}$$

$$\mathrm{Normal}(\varepsilon, \beta, \sigma) = \frac{C}{\sigma}\exp\left[-\frac{1}{\theta^2\sigma^2}|\varepsilon|^2\right],$$

where ε is the error term, β is a vector of regression parameters, σ is the standard deviation of the error term and k and n are kurtosis parameters. C and θ are normalizing constants. The GED distribution is less restrictive than the normal as it accommodates fat tails, or, kurtosis, although it does not accommodate skewness. The GED allows the maximum likelihood estimation algorithm to estimate the optimal k, where k is fixed at 2 for the normal distribution. Student's t-distribution also accommodates kurtosis with a flexible parameter, n. An inspection of Table 1 shows that kurtosis, not skewness, is the determining factor for the non-normality of asset returns. A goodness-of-fit test using the chi-square distributed likelihood ratio test can be performed among nesting distributions, with the degrees of freedom equal to the difference in the number of parameters (one degree of freedom for the GED and normal goodness-of-fit test). The test statistic is $2(l_{\text{ged}}-\mathrm{l}_{\text{normal}})$ where l is the value of the log-likelihood function. Although not reported for brevity, the chi-squared tests for all assets are significant at p-values of 0.01 or less and show that all assets' regression residuals are better fit by the GED than the normal distribution.