PRICE INTERACTION IN STATE LEVEL RENEWABLE ENERGY CREDIT TRADING PROGRAMS

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Selected Paper prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA, July 26-28

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Abstract

Using a Vector Error Correction Model approach, relationships between REC, SREC, electricity, and natural gas prices in Massachusetts and Connecticut are estimated. Confirming previous studies, the results show that REC prices respond negatively to a shock in electricity prices. Additionally, SREC prices are determined mostly by forces outside of the estimated system. Preliminary evidence is found that REC markets across states are related, but that the markets are fragmented, possibly with high transaction costs. Further analysis is required to clarify some of the results which are currently difficult to understand.

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Over the course of the last fifteen years, a number of U.S. states have adopted policies for encouraging the use of renewable energy sources. As of March 2015, 29 states and the District of Columbia had some form of Renewable Portfolio Standard (RPS) in place. Eight more states had declared goals to achieve standards in the near future (Database of State Incentives for Renewables & Efficiency 2015) (Figure 1). RPS programs generally require retail electricity suppliers to provide a minimum percentage of total generation from renewable sources; suppliers comply with the requirement by redeeming an appropriate amount of Renewable Energy Credits (RECs). A utility whose electricity portfolio is entirely made up of fossil fuel sources, for example, will need to purchase an adequate number of RECs to achieve the minimum requirement set forth by the RPS. A REC is a certificate equivalent to a unit of electricity generated from an approved renewable source. RECs are produced contemporaneously with the unit of qualified electricity, but they are bought and sold separately from the electricity. This creates a distinct market in which RECs may change hands several times before they are used for compliance.

For the last decade, there has been a marked expansion in the use of tradable rights programs to address environmental goals, both in the U.S. and internationally (Goulder 2013). It is important, therefore, to understand the functionality of currently existing programs. This study helps accomplish this goal by evaluating the performance of REC markets in three different contexts: (1) how REC markets relate to electricity prices, (2) how RECs relate to each other (across states), and (3) if solar RECs are determined by exogenous forces. Previous studies have pointed out the need for more empirical analysis of the behavior of RPS programs (see for example Fischer 2010). This study contributes to the RPS literature by exploiting a modeling framework (multivariate time series analysis) which has been overlooked by previous studies.

By using a multivariate time-series approach, this study applies data-driven results to describe the three REC market relationships mentioned above. First, as Felder (2011) argues, theory suggests that the price of a REC should be positively correlated with the difference between the price paid to renewable generators and the cost of generation from renewable sources. REC prices, therefore, are expected to be negatively correlated with wholesale electricity prices. The dynamic causal relationships between REC and electricity prices are described. Second, many states allow RECs from qualified out-of-state renewable sources to be used for in-state compliance. Both the Massachusetts and Connecticut RPS rules, for example, consider any source from within the ISO-NE regional transmission organization as a qualified source. As noted by Schmalensee (2011), however, REC markets are generally fragmented and differences in prices from state to state may be large. The empirical analysis tests the hypothesis that REC markets across states are integrated. Third, some states contain solar "carve-outs" in which electricity suppliers are required to meet a certain percentage of their renewables requirement with generation specifically from solar sources. This creates a distinct trading instrument often referred to as a Solar Renewable Energy Credit (SREC). As the overall costs of generation from solar photovoltaic generation have decreased in recent years, so have SREC prices (U.S. EIA 2013). The empirical analysis permits a test of the hypothesis that SREC prices are determined mostly by exogenous forces.

Literature Review

The literature on the general structure, cost-effectiveness, and economic implications of state level RPS programs is expanding. Berry (2002), writing in the early years of RPS implementation, hypothesizes that the price of RECs should be tied to the excess cost of electricity generation from renewable sources over that of traditional sources. REC prices should represent the "cost premium" of renewable power. He also notes the potential for risk in information, performance, and market structure to distort prices.

Several studies evaluate the potential effects of RPS on various elements of the electric power sector. Palmer and Burtraw (2005), for instance, employ the Haiku electricity market simulation model to evaluate the cost-effectiveness of numerous hypothetical national RPS scenarios. They find that as the percentage requirement of the RPS increases, electricity and REC prices increase, and coal and natural gas generation decline. Nogee, Deyette, and Clemmer (2007), in reviewing studies of RPS programs, conclude that a national RPS system would reduce fossil-fuel prices (especially natural gas) and also reduce electricity prices. Noting that assumptions need to be made about RPS transparency and market structure to translate REC prices in to retail impacts, Wiser et al. (2007) estimate that RPS mandates caused retail electricity rates to increase between zero and one percent for the seven states considered. Chen et al. (2009) review 31 analyses of RPS impact. They indicate that the majority of studies predict electricity rate increases of less than one percent, though they stress that there is large uncertainty in the estimates.

Taking a somewhat different stance from other studies, Felder (2011) explains that a more holistic approach is needed to evaluate the existence of a "price-suppression effect." This effect characterizes the displacement of higher marginal cost resources with low marginal cost renewable sources, resulting in a decrease of the wholesale price of electricity. Fischer (2010) attempts to account for the variability in studies regarding the cost impacts of RPS programs (e.g. whether RPS program increase or decrease electricity prices). She finds that the elasticity of supply from renewable sources relative to conventional sources and the stringency of the RPS help explain some of the variation in estimated cost impacts. Fischer (2010) remarks that better empirical evidence is necessary to properly evaluate the impacts of RPS programs. Assessing the efficiency of RPS programs, Schmalensee (2011) observes high levels of price dispersion between state REC prices. He concludes that this variation is a result of fragmented markets with high transaction costs.

The empirical literature on RPS programs, while growing, has resulted in inconclusive and contrasting findings regarding the relationship between REC prices and electricity prices. Other studies in the literature develop hypotheses about this relationship, as well as the interaction of REC prices across states, without any econometric or statistical techniques to test the hypotheses empirically. This lack of empirical examination of RPS programs is noted in the literature (Chen et al. 2009; Fischer 2010; Felder 2011).

REC Market Fundamentals

To provide a basic understanding of the fundamentals of the REC market, consider the simple case in which a state has an RPS requirement that 5% of its electricity must come from renewable sources. For each megawatt hour (MWh) that a renewable source generates and sells, one REC is created. For every 20 MWh of total electricity sold onto the grid, one REC must be retired. Hence, a renewable source that generates 20 MWh will have 19 surplus RECs that can be sold. These RECs would be bought by electricity suppliers whose generation portfolio contains less than 5% renewables.

In actual RPS programs there are a number of important institutional details that significantly influence REC markets. Sources eligible for REC generation are typically divided into two classes (or tiers) based on the fuel or the age of the source. Connecticut and

Massachusetts are discussed here as they are they states included in the empirical analysis. In both states, each electricity supplier must meet two different requirements; percentage requirements from Class I sources and from Class II sources. Class I RECs can be used for compliance with the Class II requirement, but the reverse is not true. Eligible generation sources in the Massachusetts RPS include geothermal, solar thermal, solar PV, wind, biomass, hydroelectric, and waste-to-energy. The MA Class I REC distinction requires that the source of generation be installed after December 31, 1997 (Database of State Incentives for Renewables & Efficiency 2015). Connecticut accepts similar sources of electricity generation, but the CT Class I distinction requires that the source be specifically from solar, wind, fuel cells, geothermal, ocean thermal, tidal, small hydroelectric facilities, and a few other advanced technologies (but not waste-to-energy or older hydroelectric plants). The Massachusetts RPS also contains provisions for a solar "carve-out" in which a certain percentage of Class I requirements must be met from solar sources, creating the MA SREC trading instrument. Connecticut does not contain such a provision. An important feature of both the CT and MA RPS programs is that both Class I requirements can be met with RECs that were generated by sources within the ISO-NE RTO (eligible sources do not necessarily have to be in-state). A wind turbine in CT, for example, produces electricity that is eligible to qualify for a MA Class I REC. The Massachusetts SREC, however, only accepts eligible in-state sources.

MA and CT RECs can be banked for up to two years; giving a useful life of three years to each REC. The year in which the REC is generated is called its "vintage," for instance a REC generated in 2011 would be a Vintage 2011 REC and could be used for compliance in 2011, 2012, or 2013. In this study, the price of a current-year vintage of each REC instrument is used as the price observation for a given time period. As a penalty for non-compliance, states generally charge an Alternative Compliance Payment (ACP) to suppliers who fall short of their requirement. The level of the ACP in MA is adjusted annually based on the Consumer Price Index. The latest ACP rate for the MA Class I standard is $67.07/MWh for the 2015 compliance year. Connecticut has a fixed Class I ACP at $55/MWh. The ACP essentially creates a price cap for RECs, as any electricity provider that is short of the requirement would typically pay the ACP if faced with a REC price that exceeds the ACP.

Conventional economic theory helps provide insights into REC price formation. REC prices are determined by supply and demand conditions in the REC market. The key to understanding REC prices lies in the dependence of the supply and demand of RECs on the market for wholesale electricity (and in turn, on the markets for renewable and conventional generation).

Basic economics of the REC market are depicted in Figure 2. The total marginal revenue received by a renewable electricity producer (the vertical axis) is equal to the sum of the REC price and the electricity price ($P_R + P_E$). The demand for RECs is largely a function of the RPS requirement, which is determined by the state legislature (Lamontagne 2013). For a given RPS requirement, the annual aggregate demand curve for RECs is a step function in which the REC price (P_R) is equal to the ACP for quantities less than the RPS requirement and falls to zero above the requirement. The simplified demand curve in Figure 2 excludes the possibility that firms may demand RECs in excess of their percentage requirement to give the appearance of being "green" or environmentally friendly.

The quantity of RECs supplied is directly proportional to the amount of qualified renewable energy generation. For illustrative purposes, the shape of the three supply curves in Figure 2 follow those outlined in New England States Committee on Electricity (2012) for wind.

In the case of a high, medium, or low level of renewable energy generation, the supply of RECs follows supply curve S_R^3, S_R^2, or S_R^1. In the case of a relatively low level of qualified renewable generation, the REC price will fall at or near the ACP. For a high level of renewable generation, the REC price will be near zero, and the renewable producer will receive only the price of electricity.

Assuming that renewable generation is more costly than conventional (nuclear, natural gas, or coal) generation, Berry (2002) states that REC price should represent the cost premium of renewable sources over their conventional counterparts. Felder (2011) claims that REC prices should be determined by the difference between the cost of renewable generation and the revenue obtained by generating the electricity. These two statements are not mutually exclusive. In Felder's framework, a decrease in the price of electricity leads to an increase in the price of RECs. The fall in electricity prices may have been caused by a decrease in the cost of conventional generation. Another possibility is that the fall in electricity prices was caused by a decrease in demand for electricity. As the RPS requirement is defined as a percentage of total electricity supplied to end-users, this would shift the RPS requirement in Figure 2 to the left. Both scenarios would lead to an increase in the price of RECs.

An increase in the supply of RECs corresponds to an increase in the supply of renewable generation. In Figure 2, this increase in supply of RECs would decrease the REC price, ceteris paribus. This outward shift in the supply curve for electricity, however, should also lead to a decrease in the price of wholesale electricity, which Felder (2011) calls the price-suppression effect. Following Felder (2011), this would lead to an increase in the price of RECs. The effect of a renewable electricity supply shock on REC prices therefore depends on the magnitude of the price suppression effect.

Data

The empirical analysis is based on five endogenous price variables. Graphs of the five endogenous price series are presented in Figure 3. Weekly REC and SREC prices based on trade data, or derived from indicative quotes when trades are unavailable, are used in the study (Skystream Markets 2014). These price data are the midpoint between bid and offer prices for current-year vintages reported by Skystream Markets. Unfortunately, data for volume of trades is unavailable. Two Class I REC price series are included (Connecticut and Massachusetts). The Massachusetts SREC price series is also included. These price series are for the period March 2011 to December 2013. The U.S. Energy Information Administration (U.S. EIA 2014) publishes wholesale electricity trades in the ISO-New England (ISO-NE) regional transmission organization (RTO). A weighted average is constructed based on daily price and volume traded to provide a weekly wholesale electricity price for the region (MassHub); this is the fourth endogenous price series. Natural gas spot price (NG) data from the Algonquin Hub in Massachusetts (Bloomberg 2015) is included as the final endogenous variable to capture the costs of conventional generation. Additionally, data on cooling and heating degree days for the New England region, which roughly aligns geographically with the ISO-NE RTO, is provided by the U.S. National Oceanic and Atmospheric Administration (U.S. NOAA, 2014). Cooling and heating degree days are employed as exogenous variables in the model. All endogenous series are in natural logarithms in the empirical analysis.

The REC price dataset contains 47 missing observations (32% of total observations). The previous week's price observation is used to fill in the missing values.

Methodology

The vector error correction model (VECM) provides a flexible framework to characterize the three REC market relationships outlined above. The VECM (Juselius 2006) takes the form

$$\nabla Y_t = \gamma + \sum_{i=1}^{k-1} \Gamma_i \nabla Y_{t-i} + \Pi Y_{t-1} + \lambda X_t + \varepsilon_t \tag{1}$$

where

Y_t represent the endogenous variables;

n is the number of endogenous variables;

m is the number of exogenous variables;

∇Y_t is a $(n \times 1)$ vector of first differences of the endogenous series;

γ is a $(n \times 1)$ vector of constants;

∇Y_{t-i} represents lagged values of order i;

Γ_i is the corresponding $(n \times n)$ coefficient matrix;

k is the optimal number of lags in a levels vector autoregressive representation;

X_t is a $(m \times 1)$ vector of exogenous series (cooling and heating degree days);

ε_t is a $(n \times 1)$ vector of innovations;

ΠY_{t-1} is known as the "error correction" term, where Π is $(n \times n)$ and Y_{t-1} is $(n \times 1)$.

The VECM allows long-run, equilibrium relationships among the variables to be characterized by examining the existence of cointegration. Cointegration is present when there exists at least one linear combination of non-stationary, I(1) variables which is itself stationary, I(0) (Tsay 2014). A key assumption for the estimation of a VECM is that the endogenous variables (Y_t) are non-stationary, but that they are stationary in first differences (∇Y_t).

Decomposing Π as

$$\Pi = \alpha\beta' \tag{2}$$

where α and β are both $(n \times r)$ matrices gives an interpretation of the long-run relationships among the endogenous series and r is the rank of Π. Because Y_{t-1} is non-stationary and ∇Y_t is stationary, $\alpha\beta'$ contains stationary linear combination(s) of the n endogenous variables, provided cointegration is present. The r columns of β are known as the cointegrating vectors (Tsay 2014). Statistical tests are performed on Π, α, and β to determine r, and to further characterize the long-run structure between the endogenous series (Juselius 2006; Mjelde and Bessler 2009).

One such test is for variable exclusion, where the null hypothesis is that a particular series is not in the cointegrating space,

$$H_0\colon E'\beta = 0 \tag{3}$$

where E is a matrix containing zero restrictions for excluding a particular series from the cointegrating space. Failure to reject the null hypothesis for a given series implies that the corresponding series is excluded from the long-run relationships characterizing the system.

Another statistical hypothesis is weak exogeneity; the null is that a particular series does not adjust to disruptions in the long-run relationships. Since β contains the parameters characterizing these long-run relationships, α is made up of the parameters which describe how the series adjust to disruptions, bringing the long-run relationships back to equilibrium. The null hypothesis of the test for weak exogeneity is

$$H_0\colon W'\alpha = 0 \tag{4}$$

where W, like E, contains zero restrictions for excluding the corresponding α parameters for a particular series. A failure to reject the null hypothesis for a given series implies that the corresponding market does not respond to deviations from the long-run equilibrium relationship.

A third test useful for examining the cointegrating space is a test for variable stationarity. The null hypothesis of this test is that at least one of the cointegrating vectors exists because a particular variable is itself stationary. In other words, the cointegrating vector does not represent a stationary linear combination of non-stationary variables, but rather a transformation of an otherwise stationary variable.

In addition to statistical tests concerning the cointegrating space, innovation accounting procedures (impulse response functions and forecast error variance decompositions) are helpful in characterizing the relationships among the markets. Impulse response functions (IRFs) show the effect of a one-time shock in one variable on the future values of the remaining variables. Forecast error variance decompositions (FEVDs) measure the percentage of forecast error for a given series that is explained by shocks to each of the other series. To conduct these innovation accounting procedures, the VECM in equation (1) is rewritten in a levels vector autoregressive (VAR) form, i.e.

$$Y_t = \gamma + (1 + \Pi + \Gamma_1)Y_{t-1} - \sum_{i=1}^{k-2}(\Gamma_i - \Gamma_{i+1})Y_{t-i+1} - \Gamma_{k-1}Y_{t-k} + \lambda X_t + \varepsilon_t \tag{5}$$

An issue that arises when conducting innovation accounting procedures is that the contemporaneous covariance matrix of ε_t in equation (5), Σ_ε, is usually not a diagonal matrix in empirical applications (the components of the error term are contemporaneously correlated). If this is the case, then any particular series cannot necessarily be shocked without affecting another series; innovation accounting procedures are nonsensical if contemporaneous correlation exists (Tsay 2014). To overcome this limitation, the innovations ε_t must be orthogonalized. Consider a Bernanke (1986) ordering, where the correlated innovations ε_t are written as a function of the underlying orthogonal sources of variation, σ_t,

$$\varepsilon_t = A^{-1}\sigma_t \tag{6}$$

To conduct the innovation accounting procedures, the VAR representation of equation (1) is pre-multiplied by the matrix A.

The matrix A is obtained through causal flow methods (Pearl 2000; Spirtes et al. 2000). Directed Acyclic Graphs (DAGs) provide a visual summary of contemporaneous causal flows among innovations from the estimated vector error correction model. The GES algorithm in TETRAD V (2015) is employed to generate a DAG using the covariance matrix of error terms from the estimated VECM (Chickering 2003). In DAGs, an arrow from A to B implies that A causes B. An undirected line from A to B with no arrow (or a line with an arrow on each end) signifies flows between the two, but the algorithm cannot determine whether A causes B or B causes A. If there is no information flow between A and B, the algorithm will not generate a line of any type connecting the two. The GES algorithm starts from a DAG representation where all variables are independent of each other (no lines), and searches over more complicated representations for improvements in the Bayesian Information Criterion (BIC). The algorithm picks the DAG representation such that no added line or change of direction improves the BIC.

Several of the results from this empirical analysis will shed light on the first question, whether REC prices are related to electricity prices. First, the existence of cointegration would imply that REC and electricity prices move together in the long-run. Statistical tests for variable exclusion further investigate whether a particular price series is included in the estimated long-run relationships. Tests for weak exogeneity will show whether electricity prices, for instance, respond to disruptions in the long-run relationships. Further, DAGs show how the endogenous price series are related in contemporaneous time. Impulse response functions show the direction of effects of an increase in a particular series on all the other endogenous series over time. Finally, forecast error variance decompositions show the percentage of forecast error of each seiries can be explained by shocks in the other series.

Similarly, the second research question, whether REC prices across states are integrated, can be answered in a number of ways using this empirical approach. Perhaps most importantly, the existence of cointegration, along with tests for variable exclusion and weak exogeneity, would provide statistical evidence that there is a long-run equilibrium relationship among REC prices. DAGs and innovation accounting procedures further characterize the relationships across state REC prices.

Lastly, the question of whether SREC prices are determined mostly by exogenous forces can be addressed. Given cointegration, the tests for variable exclusion and weak exogeneity help in examining if SREC prices are a part of the estimated long-run relationships, and whether they respond to disturbances in these relationships. DAGs show any contemporaneous causal flows involving SREC prices. Impulse response functions show whether changes in REC or electricity prices have effects on SREC prices over time, and forecast error variance decompositions demonstrate the percentage of forecast error in SREC prices that is accounted for by other series in the model. If SREC prices are determined most heavily by exogenous forces (e.g. costs of generation), one might expect impulse response functions to be near zero and forecast error variance decompositions to show minimal contributions from other series.

Results and Discussion

The empirical analysis will be used to consider three basic questions about the Massachusetts and Connecticut REC markets: 1) the relationship between REC prices and electricity prices (expected to be negative); 2) the relationship between the REC prices in two states (expected to be positive); and 3) the MA SREC price, with the expectation that the price is driven primarily by exogenous forces.

The results of Augmented Dickey-Fuller tests for stationarity of the five endogenous series are reported in Table 1. The series are non-stationary in levels, but stationary in first differences, justifying the potential for cointegration and the use of the VECM framework. A two-step procedure is followed to test for cointegration. First, the optimal lag length (k) in a VAR(k) representation for the data is first specified. Using the Hannan and Quinn loss metric, the optimal lag length (k) is one. As the construction of impulse response functions is an important part of this analysis, the VECM form in Eqn. (1) instead uses $k = 2$ so as not to eliminate the Γ_i parameters from the model completely. Next, the cointegrating rank (r) is determined following the trace test of Johansen (1991). Results of this procedure are reported in Table 2. Two cointegrating vectors ($r = 2$) are chosen. The remaining discussion of the empirical results is based on a VECM specification in Eqn. (1) with $k = 2$ lags and $r = 2$ cointegrating vectors.

The null hypothesis of variable stationarity is rejected at the 5% level for all series except CT Class I REC (Table 3). It is possible that one of the cointegrating relationships arise from the fact that the CT Class I REC series is stationary itself. The null hypothesis of variable exclusion cannot be rejected at the 5% level for the MA Class I REC, CT Class I REC, and MA SREC series (Table 3). This implies that the estimated long-run relationships between these REC prices might be the result of integration between natural gas and electricity prices. The null hypothesis of weak exogeneity is rejected at the 5% level for all series except MA SREC. The MA SREC price series is the only series that does not respond to disruptions in the estimated long-run relationships. This is consistent with the idea that SREC prices are determined mostly outside of the system. The most likely exogenous force is the cost of solar generation. Both CT and MA Class I REC prices respond to disruptions in the system.

To carry out innovation accounting procedures, the contemporaneous causal structure of innovations is inferred using graphical techniques (DAGs). The contemporaneous causal structure generated by the GES algorithm is shown in Figure 4. The DAG shows that MassHub electricity prices move natural gas prices in contemporaneous time. There are additional contemporaneous causal flows from MA SREC prices to electricity prices. Causal flows between MA Class I REC prices and CT Class I REC prices are present, but the direction of flows was unable to be determined. Since the MA and CT Class I requirements both allow RECs from out-of-state (but within the ISO-NE RTO), and the MA ACP is approximately $10/MWh higher than the CT ACP, it is expected that an electricity supplier in MA would purchase RECs in the CT market before paying the (higher) ACP rate in MA. As such, the matrix A in equation (6) allows for contemporaneous causal flows from MA Class I RECs to CT Class I RECs.

Impulse response functions (IRFs) are presented in Figure 5 and forecast error variance decompositions (FEVDs) are presented in Table 4. IRFs suggest that neither the CT Class I REC nor the MA Class I REC price respond heavily to shocks in electricity prices. The responses are negative. This direction is consistent with Felder (2011), who hypothesizes that REC prices should be negatively related to electricity prices. The FEVDs suggest electricity prices explain only 0-3% of forecast error variance in either of the two series.

The IRFs and FEVDs provide some evidence that the CT and MA Class I REC markets are related. The MA Class I REC price explains approximately 59% of the forecast error variance in CT Class I REC prices at a one-week forecast horizon (this decreases to 42% at a 12-week horizon). CT Class I RECs, however, explain only 0-7% of the variation in MA Class I RECs at one to 12-week horizons. Additionally, the IRFs show that CT Class I REC prices respond positively to shocks in MA Class I REC prices, but that MA Class I REC prices respond negatively to shocks in CT Class I REC prices. The asymmetric relationships between these REC prices is surprising since, as noted above, Connecticut allows RECs from qualified generation in Massachusetts, and vice versa. An explanation for this finding might be that the MA REC market drives the CT REC market because of the nature of the RPS rules and the fact that MA has a larger amount of renewable generation. The U.S. EIA (2012) reports that Massachusetts had 0.566 GW of renewable capacity in 2010, about twice as much renewable generating capacity as Connecticut (0.281 GW). A second explanation is the assumed direction of the undirected arrow in the DAG. Results not presented here suggest this is an important issue.

The IRFs show that the MA SREC price does not respond heavily to the other endogenous series. The FEVDs corroborate this finding; less than 2% of forecast variance in MA SREC prices is explained by the other endogenous series at any forecast horizon. These findings, along with the variable exclusion an weak exogeneity tests, suggest the SREC market is exogenous to the system.

In summary, evidence is found supporting the idea that an increase in electricity prices results in decreasing REC prices. The estimated effect, however, is small. Additionally, the empirical results show that MA SREC prices are mostly exogenous in the context of the estimated model. MA SRECs do not respond to shocks in other price series or to disruptions in long-run relationships. This is consistent with the notion that SREC prices generally represent the cost of solar generation. Mixed evidence is found regarding the question of whether REC prices are integrated across states. The trace test of Johansen (1991) resulted in two cointegrating vectors characterizing the long-run relationships between the five endogenous price series. The MA and CT Class I REC prices are found to respond to perturbations in these relationships. Both series, however, are excluded from the cointegrating space when considering a statistical test for variable exclusion. An asymmetric relationship between MA and CT Class I REC prices is found as well (CT prices respond negatively to MA prices, MA prices respond positively to CT prices). One explanation for these mixed results is that REC markets in MA and CT are fragmented, with high transaction costs, as Schmalensee (2011) indicates.

Overall, taking the results from this study and previous studies indicates that REC markets may still be in their infant stages. It appears transaction costs are large in the market. Further, research into transaction costs is necessary, be it from how REC markets operate to regulations on ability to transfer RECs between states. The finding that REC prices between MA and CT are not cointegrated suggests that markets have not matured to the point of being efficient.   A limited number of transactions may be limiting market integration.

Two results from the IRFs and FEVDs are counter intuitive. It is not clear why the other endogenous series respond heavily to shocks in MA SREC prices. Second, the natural gas price has almost no effect on any of the other prices, even the MassHub electricity price. Previous studies such as Mjelde and Bessler (2009) found much stronger relationships between fuel generation prices and electricity prices

It is possible that other empirical methodologies are better suited to handle REC prices. Specifically, the MA and CT Class I REC price series are relatively flat in the second half of the sample (hovering near the ACP). In addition, there may be spurious correlation between MA SREC prices and natural gas prices as both prices have been decreasing for different reasons over the time period. Addressing these issues is necessary to help clarify some of the empirical results which are currently difficult to understand.

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Table 1. Results of tests for presence of unit root.

	LN(series)		FD(LN(series))	
Series	Test Stat	P-value	Test Stat	P-value
ISO-NE				
CTClassI	-1.92	0.61	-6.33	0.01
MAClassI	-1.77	0.67	-6.06	0.01
MASREC	-1.39	0.83	-6.99	0.01
MassHub	-2.88	0.05	-4.71	0.01
NG	-2.10	0.28	-4.59	0.01

Note: All series were tested using the Augmented Dickey-Fuller Test (Fuller 1996). The null hypothesis of each test is that a unit root is present. A constant and time trend component were included in the tests for CTClassI, MAClassI, and MASREC. A constant only was included in the tests for MassHub and NG.

Table 2. Results of trace test for lag order $k = 2$

r	Trace	Critical Value (5%)	P-Value
0	155.052	100.009	0.000
1	74.320	73.016	0.040
2	35.843	49.960	0.480
3	18.030	30.775	0.596
4	5.679	15.251	0.694

The null hypothesis for each $i = 0,1, \dots ,4$ is that $r \leq i$. The first failure to reject occurs at $r \leq 2$, therefore two cointegrating vectors are selected.

Table 3. Test for variable exclusion, stationarity, and weak exogeneity. P-values in parentheses.

Test	CT Class I	MA Class I	MA SREC	MassHub	NG
Exclusion	3.280	3.479	1.401	56.098	58.658
	(0.194)	(0.176)	(0.496)	(0.000)	(0.000)
Weak Exogeneity	18.053	20.678	1.602	11.008	26.639
	(0.000)	(0.000)	(0.449)	(0.004)	(0.000)
Stationarity	10.506	11.260	13.685	22.723	25.372
	(0.062)	(0.046)	(0.018)	(0.000)	(0.000)

Table 4. Forecast Error Variance Decompositions

		Contribution of				
Series	Weeks Ahead	CT Class I	MA Class I	MA SREC	MassHub	NG
CT Class I	1	41.324	58.676	0.000	0.000	0.000
	4	45.049	52.256	0.359	1.528	0.809
	8	42.669	49.379	4.214	2.451	1.288
	12	35.802	42.335	18.454	2.261	1.149
MA Class I	1	0.000	100.000	0.000	0.000	0.000
	4	1.025	97.964	0.743	0.234	0.034
	8	3.942	86.221	9.583	0.219	0.035
	12	7.447	66.088	26.242	0.152	0.070
MA SREC	1	0.000	0.000	100.000	0.000	0.000
	4	0.107	0.206	98.843	0.379	0.465
	8	0.242	0.363	98.500	0.452	0.444
	12	0.401	0.512	98.107	0.517	0.463
MassHub	1	0.000	0.000	0.000	100.000	0.000
	4	0.155	0.159	1.668	89.751	8.267
	8	0.139	0.151	12.031	80.301	7.378
	12	0.149	0.180	24.382	68.922	6.368
NG	1	0.000	0.000	6.812	28.090	65.098
	4	0.554	0.590	8.622	33.720	56.513
	8	1.678	0.532	24.990	37.116	45.685
	12	2.686	0.408	41.160	20.814	34.931

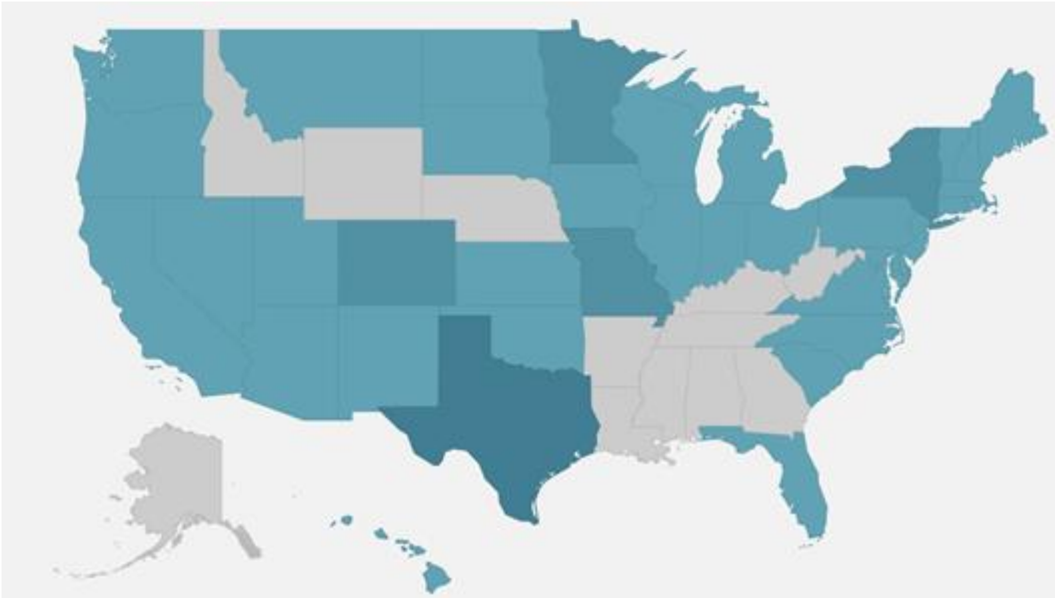

Figure 1. States with either an established RPS program or a goal to achieve standards
Source: Database of State Incentives for Renewables & Efficiency (2015)

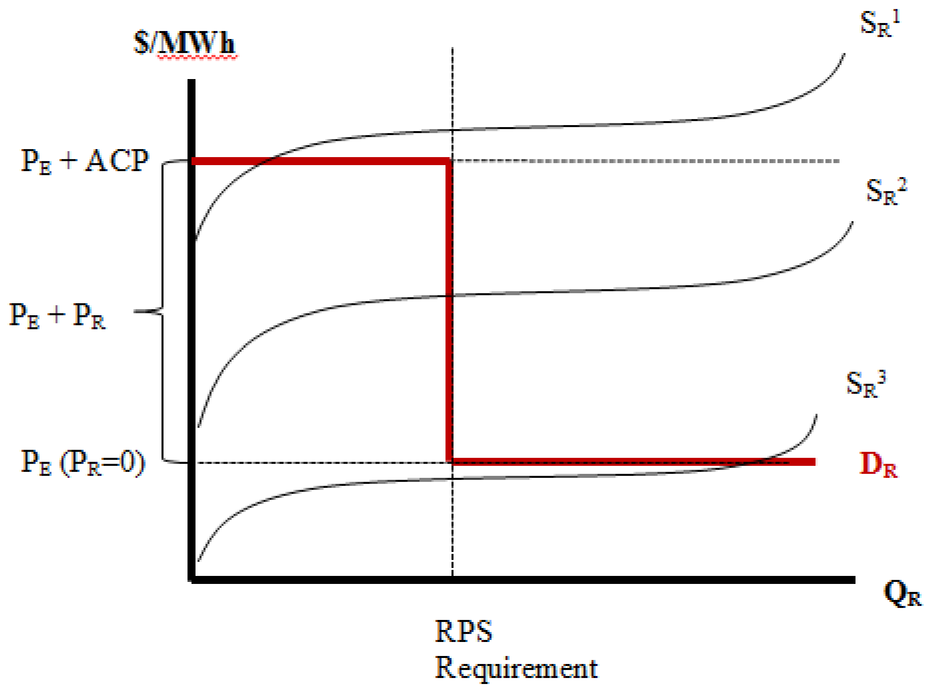

Figure 2. REC market supply and demand fundamentals

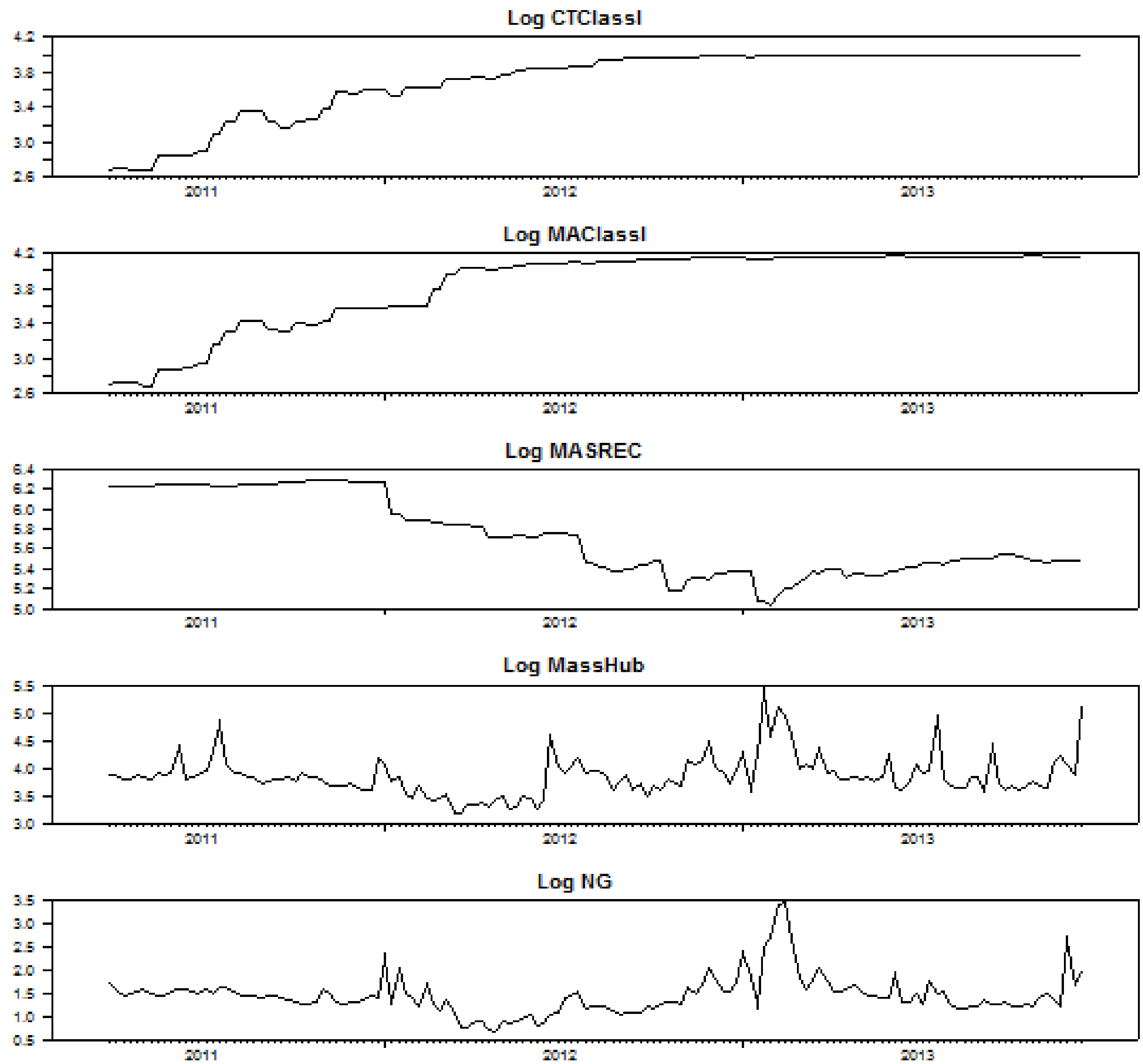

Figure 3. Endogenous price series used in estimating the vector error correction model

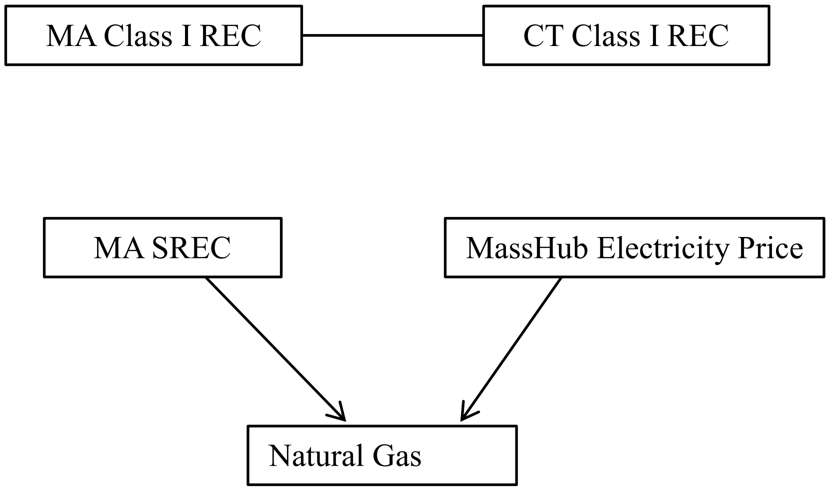

Figure 4. **Directed Acyclic Graph (DAG) for contemporaneous causal flows among innovations from the estimated vector error correction model**

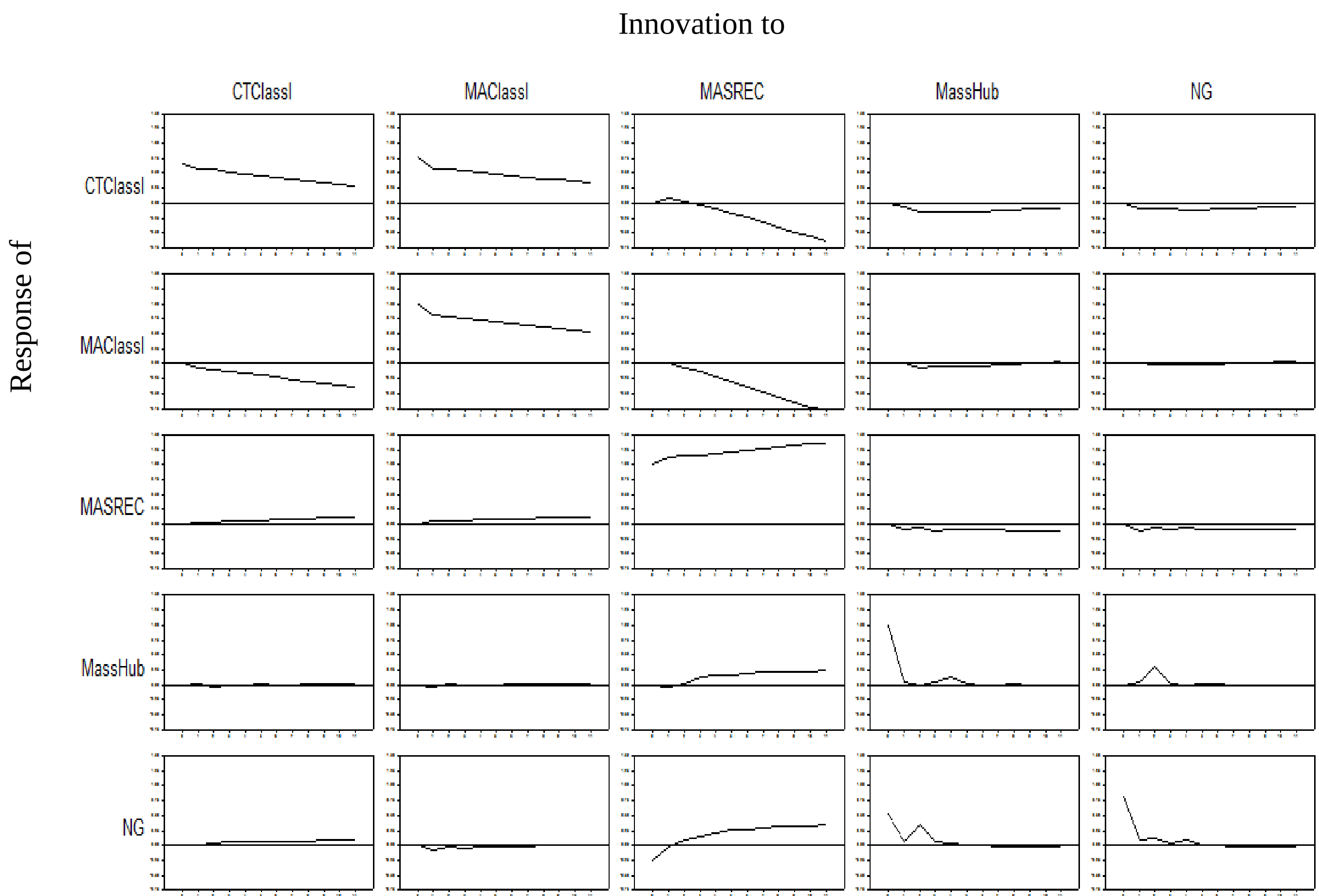

Figure 5. Impulse response functions from the vector error correction model