Diversification in Electricity Price and Volume Swaps

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This analysis determines the effect of diversification on portfolios of retail electricity price and volume swaps. These contracts are used by municipalities to provide fixed costs to customers and enables greater renewable generation. Power marketing firms often pay the floating generation cost. We find very limited benefits to diversification for power marketing firms providing these swaps within the NEPOOL region. This evidence supports a long/short swap strategy, or diversification across wide geographic regions.

JEL Codes: G12; G10

Keywords: Electricity Derivatives; Renewable Energy

1 Introduction

This analysis highlights the role of power marketing firms, which can enter into contracts across various electricity markets, in reducing risk for consumers. They do so by offering fixed for floating electricity swaps. These swaps allow retail customers to pay a fixed certain price for their uncertain electricity demand. This reduction in risk is important to increase the proportion of intermittent renewable energy used in deregulated power markets. Thus, our analysis contributes to the literature on methods to provide stable electricity prices to end consumers, thereby facilitating economic growth.

Valuation of these swaps is an active area of research. Difficulties arise from both the unique behavior of electricity prices as well as the uncertain volume of the contract. A step toward such valuation is Nazar et al. 2018 which created a method to simultaneously forecast both power and load. Our present analysis adds to the literature not by valuing individual contracts, but by determining how a portfolio of these contracts behaves. Is there a substantial diversification benefit, and over how wide of a geographic region must a power marketing firm diversify?

Anderson, Hu, and Winchester 2007 discuss the important role forward contract play in electricity markets. Benth and Koekebakker 2008 use a Heath-Jarrow-Morton approach to model fixed-for-floating electricity price swaps to some success. Note, in this analysis the size of the swap (megawatt hours) is fixed. Kemper, Schmeck, and Kh.Balci 2022 price derivatives based on electricity swaps in an arbitrage-free framework by introducing a market price for the delivery period of the electricity swap.

Frestad, Benth, and Koekebakker 2010 find evidence of substantial risk-premia in short-dates swaps on Nordic exchanges. They also find evidence that daily swap returns exhibit significant kurtosis, but little skewness. Similarly, Blanco, Peña, and Rodriguez 2018 find evidence that electricity swap Value-at-Risk (VaR) estimates underestimate tail risk if a Normal distribution is used. Peña, Rodríguez, and Mayoral 2020 determine that, at least with respect to electricity futures, decent VaR estimates can be made with a GARCH(1,1) model with Student-t errors.

Note, our present analysis contributes to risk-management and mitigation by investigating the effect of diversification in electricity swaps. In addition to lessening risk, portfolios tend to have return distributions that are closer to the Normal distribution when compared to single asset return distributions.

There is a substantial amount of research on how to incorporate intermittent renewable energy into deregulated power markets. Lai et al. 2021 investigate a portfolio hedging strategy for natural gas generators in the presence of intermittent renewable energy. Ihlemann et al. 2022 highlights the benefits of balancing power capacity markets across borders—thereby diversifying across a larger region. Zeynali et al. 2021 investigate the power price effect of coordinating wind generation with electric vehicle charging. Successful integration of renewable energy has a positive effect on regional economic growth. González and Alonso 2021 discuss the effect of power market integration on industrial power prices.

The remainder of this paper is organized as follows. Section 2 describes the swap contract, and section 3 covers our dataset and empirical methods. Section 4 presents results and section 5 concludes.

2 Swap Description

The contract is a fixed for floating power swap, and is based on contracts presently being traded by power marketing firms and municipalities. The contract has the following characteristics:

- Revenue per MWh supplied is fixed.
- Cost of supplying power is floating.
- Amount of power supplied is floating.
- Customers can *migrate* onto and away from the load that must be served.

We can write the payoff on the contract as:

$$Profit = (P - X)T_{MWh}$$

where P is the power price in \$/MWh, X is the price for which we must deliver power in \$/MWh, and T is the amount of power we must deliver in MWh. Further:

$$T_{MWh} = f(E, I)$$

where E and I denote weather and migration respectively. Migration itself is a function of the power price. If the retail power price increases, then consumers migrate to the fixed contract, and they leave the fixed contract as the price decreases.

The Effect of a Load Changes on Profit

A load increase will increase the cost of power reducing profit per MWh. In addition there is lower profit (or a loss) on a larger amount of MWh. Thus, load increases tend to lower profit.

Alternatively, a decrease in the load will lower prices and increase profit per MWh. However this increased profit will be earned on fewer MWh, so ultimately, it is unclear whether total contract profit will increase or decrease.

Thus the contract tends to earn the most profit when load and power prices do not deviate much from those specified in the contract. The contract then has an analogue in the butterfly, and short straddle option spreads. In this analysis, we set the fixed contract price as the average price of power in the year prior and discount it by a 15% cost of capital.

3 Data and Methods

Our analysis uses monthly Real-Time Locational Marginal Prices (RT-LMP) ranging from January 2016 to February 2022, for 74 total months. Our RT-LMP cover each region in the area overseen by the New England Independent System Operator (ISO-NE). These regions are: Maine, Connecticut, Vermont, New Hampshire, Rhode Island, South-East Massachusetts, North-East Massachusetts, and West-Central Massachusetts. Data are gathered directly from the ISO New England's ISO Express data service[1]. Summary statistics of the swap contract changes calculated using each region's RT-LMP are in table 1 below.

Table 1: Summary Statistics: Real-time monthly LMP changes by region in \$/MWh. January 2016 through January 2022 inclusive.

	ME	NH	VT	CT	RI	SEMA	WCMA	NEMA
count	73.00	73.00	73.00	73.00	73.00	73.00	73.00	73.00
mean	1.73	3.28	1.32	3.42	3.50	3.52	3.27	3.32
std	396.04	84.78	59.92	90.14	73.97	80.76	103.25	129.29
min	-2354.74	-207.97	-195.96	-289.89	-231.78	-202.51	-330.64	-479.08
25%	-33.82	-38.49	-29.90	-27.09	-42.67	-40.24	-35.88	-45.76
50%	1.17	0.11	-1.42	0.64	0.86	-0.88	0.44	5.79
75%	21.52	24.86	30.71	38.02	43.52	36.81	44.46	39.89
max	2322.53	207.61	187.38	295.33	254.35	298.51	337.05	606.29

Table 2: Correlation Matrix: Real-time monthly LMP changes.

	ME	NH	VT	CT	RI	SEMA	WCMA	NEMA
ME	1.00	0.09	0.05	0.02	0.05	0.06	0.05	0.03
NH	0.09	1.00	0.72	0.62	0.57	0.50	0.55	0.49
VT	0.05	0.72	1.00	0.41	0.45	0.35	0.37	0.41
CT	0.02	0.62	0.41	1.00	0.78	0.61	0.92	0.85
RI	0.05	0.57	0.45	0.78	1.00	0.70	0.77	0.69
SEMA	0.06	0.50	0.35	0.61	0.70	1.00	0.65	0.58
WCMA	0.05	0.55	0.37	0.92	0.77	0.65	1.00	0.90
NEMA	0.03	0.49	0.41	0.85	0.69	0.58	0.90	1.00

The correlation coefficients between ISO-NE locations ranges from 0.029 between Connecticut and Maine, to 0.86 between northeast and west-central

[1] https://www.iso-ne.com/markets-operations/iso-express

Massachusetts. Generally, Maine has the smallest correlation with the rest of New England. This makes Maine attractive for diversification, however Maine also has the highest volatility.

Results from Jarque-Bera tests for Normality are in table 3 below. Over each region we reject the null, which is evidence that the price difference series do not have skewness and kurtosis consistent with the Normal distribution. Notably, however, electricity returns (over periods with positive prices) also generally fail Normality tests, as do individual stock returns.

Table 3: Jarque-Bera Test for Normality Results

	ME	NH	VT	CT	RI	SEMA	WCMA	NEMA
JB Stat	2972.29	4.67	12.84	28.05	9.19	17.0	36.42	203.31
p-value	0.00	0.10	0.00	0.00	0.01	0.0	0.00	0.00

4 Results

4.1 Single Zone Results

Below we provide results for each zone, and long-only and long-short portfolios across all zones. We use the Sharpe Ratio as a measure of portfolio performance.

Table 4: Contract percentage profit, individual zone data.

Zone	Mean Return	Standard Deviation	Sharpe Ratio
Maine	1.110617	1.088223	1.020579
New Hampshire	0.715642	0.154146	4.642614
Vermont	0.761109	0.250510	3.038240
Connecticut	0.695537	0.225178	3.088828
Rhode Island	0.689433	0.174560	3.949548
SE Massachusetts	0.763188	0.255090	2.991837
WC Massachusetts	0.712360	0.168011	4.239960
NE Massachusetts	0.753476	0.375916	2.004372
Average	0.77517025	0.33645425	3.1219973

The Sharpe Ratio for Maine is the lowest at `1.02`. The Sharpe Ratio for New Hampshire is the highest at `4.64`. These Sharpe Ratios are relatively high and reflect our construction of the contract—Sharpe Ratios would likely be lower if we did not reset the contract costs after each year.

4.2 Portfolio Results

We construct both long-only and long-short portfolios. Typically power marketing firms take the long side of these contracts, and municipalities and other sources of load take the short side. That said, through trading with other power marketing firms, it is possible for a firm to take a short position. It may be realistic, however, to limit the amount which can be sold.

We calculate mean-variance optimal portfolios by maximizing the Sharpe ratio (using Martin 2021). This method assumes quadratic utility or asset returns are Normally distributed (or a member of the elliptical family of distributions). That is, we assume investors are indifferent to the third, and higher moments of the return distribution. This assumption is common when dealing with stock portfolios, despite evidence that stock returns may exhibit significant skewness and kurtosis. The assumption is likewise troublesome when applied to electricity returns and the returns on our swap contracts.

4.2.1 All Zone Portfolio

Below are results for long-only and long-short portfolios. A long-only portfolio is more consistent with the role of a power-marketing firm, however these firms are able to enter the short side of the swap contract (buying rather than supplying power).

1. No Shorting

   Our long-only portfolio has a Sharpe ratio of 4.58, which is slightly less that the maximum Sharpe ratio across individual regions (New Hampshire has a Sharpe ratio of 4.64). It is, however, greater than the average Sharpe Ratio over all regions (3.12). Somewhat counter intuitively, mean-variance optimization allocated most of the portfolio to west-central Massachusetts and Rhode Island, with a 0% weight to the region with the highest Sharpe Ratio (New Hampshire). Again these are high Sharpe ratios and should only be compared to each other given the assumptions made in the contract construction.

   Table 5: All zone portfolio, long-only portfolio.

Expected Return	73.94%
Standard Deviation	15.70%
Sharpe-Ratio	4.58

   (a) Long-only Weights Constrained to 20%

Table 6: Region weights in long-only portfolio.

Region	Weight
Maine	8.09%
New Hampshire	0.0%
Vermont	0.0%
Connecticut	0.0%
Rhode Island	22.21%
SE Massachusetts	0.0%
West-Central Massachusetts	69.70%
NE Massachusetts	0.0%

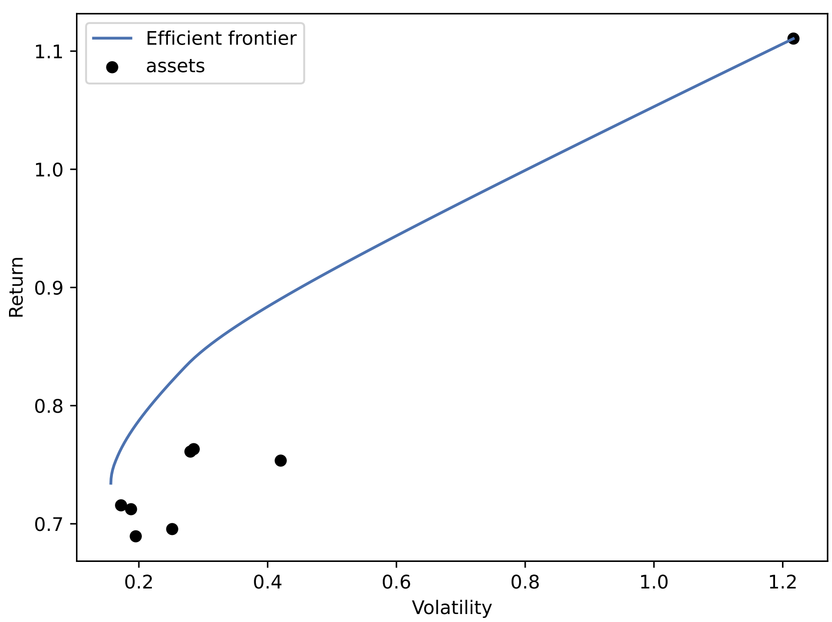

Figure 1: Long only portfolio.

In the above long-only portfolio 5 regions have 0% weights, and approximately 70% of the portfolio is in West-Central Massachusetts. Since many power marketing firms have internal rules regarding maximum exposure to any given region or contract, it makes sense to additionally restrict the weight of each region. In the table below we provide a long-only optimal portfolio with the maximum weight in any region constrained to 20%.

Constraining the weights to a maximum of 20% lowers the Sharpe Ratio to 3.95 from 4.58 in the long-only portfolio. The reduction in the Sharpe Ratio is due to an increase in the portfolio standard deviation from 15.70% to 18.47%. The expected return increased with the additional constraints. With the additional 20% constraint, only two regions (Vermont and NE Massachusetts) receive a 0% weight.

Table 7: All zone portfolio, long-only portfolio.

Expected Return	74.99%
Standard Deviation	18.47%
Sharpe-Ratio	3.95

Table 8: Region weights in long-only portfolio.

Region	Weight
Maine	8.35%
New Hampshire	20.00%
Vermont	0.00%
Connecticut	11.65%
Rhode Island	20.00%
SE Massachusetts	20.00%
West-Central Massachusetts	20.00%
NE Massachusetts	0.00%

2. Shorting Allowed

In the two portfolios below we allow the power marketing firm to take the short side of the contract. Given the generally high correlations between the contract returns across regions, allowing shorting will allow the portfolio standard deviation to be greatly reduced without lowering the mean return. That said, traditionally power marketing firms are on the long side of these types of contracts, because they are generally an arm of a power producer. The short side is typically a municipality or other load source. Therefore, the ability to take the short side of these contracts may be limited.

(a) Weights Constrained to 100%

Allowing up to 100% short positions results in a very low portfolio standard deviation and high Sharpe Ratio at 1.75% and 34.39 respectively. The optimization took advantage of the high positive correlations and allocated negative weights of approximately -82%, -92%, and -100% to New Hampshire, south-east Massachusetts, and north-east Massachusetts respectively. This is evidence that geographically-constrained power marketing firms should consider shorting these swap contracts to the extent that it is allowed by the market and corporate policy.

Table 9: All zone portfolio, full-shorting-allowed portfolio.

Expected Return	62.30%
Standard Deviation	1.75%
Sharpe-Ratio	34.39

Table 10: Region weights in shorting-allowed (constraint at 100%) portfolio.

Region	Weight
Maine	1.39%
New Hampshire	-82.03%
Vermont	72.57%
Connecticut	100.00%
Rhode Island	100.00%
SE Massachusetts	-91.93%
West-Central Massachusetts	100.00%
NE Massachusetts	-100.00%

(b) Weights Constrained to 20%

It is more reasonable for a power marketing firm to constrain the firm's exposure to a given contract and market. The portfolio below constrains the weight in each region to between -20% and 20%. When doing so the portfolio's Sharpe Ratio of 4.43 is

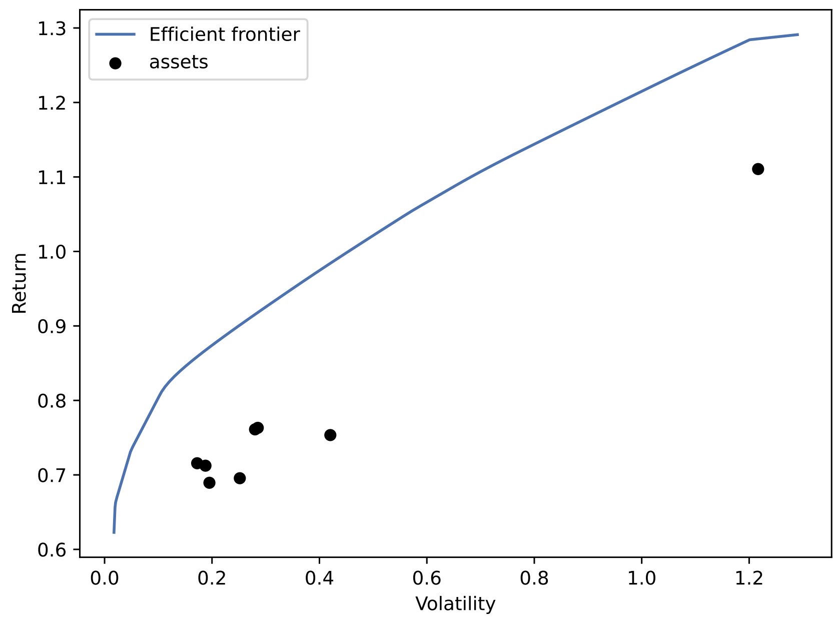

Figure 2: Full-shorting-allowed portfolio.

slightly *lower* than the Sharpe Ratio of the long-only (but otherwise unconstrained) portfolio (4.58). The only region shorted in the portfolio is north-east Massachusetts, which had the lowest individual region Sharpe Ratio after Maine.

Table 11: All zone portfolio, shorting-allowed (weights constrained to 20%) portfolio.

Expected Return	73.96%
Standard Deviation	16.22%
Sharpe-Ratio	4.43

5 Conclusion

In this analysis we have calculated returns on price and volume swap contracts which are often provided by power marketing firms to municipalities. While these contracts may have a high Sharpe Ratio individually, we have found evidence for the limited diversification potential on the New England

Table 12: Region weights in shorting-allowed (constraint at 20%) portfolio.

Region	Weight
Maine	6.52%
New Hampshire	20.00%
Vermont	13.48%
Connecticut	20.00%
Rhode Island	20.00%
SE Massachusetts	20.00%
West-Central Massachusetts	20.00%
NE Massachusetts	-20.00%

ISO for these swaps. For a power marketing firm to limit risk within the ISO, they would have to construct long-short power swap portfolios. This essentially means risk can only be allocated among similar firms, and therefore does not reduce the risk held by the overall market participants.

This highlights the need for power marketing firms to be able to diversify across geographical markets. This is often limited by differing power market structure and corporate policy. Therefore, we find support for measures which allow power marketing firms to operate with greater geographic diversity. However, a remaining question for future analyses is the extent to which greater geographic diversification can reduce risk. Specifically, measuring the effect of adding contracts on the ERCOT (Texas) or CAISO (California) operated electricity grids is a sensible area of future research.

References

Anderson, Edward J, Xinin Hu, and Donald Winchester (2007). “Forward contracts in electricity markets: The Australian experience”. In: *Energy Policy* 35.5, pp. 3089–3103 (cit. on p. 2).

Benth, Fred Espen and Steen Koekebakker (2008). “Stochastic modeling of financial electricity contracts”. In: *Energy Economics* 30.3, pp. 1116–1157 (cit. on p. 2).

Blanco, Iván, Juan Ignacio Peña, and Rosa Rodriguez (2018). “Modelling electricity swaps with stochastic forward premium models”. In: *The Energy Journal* 39.2 (cit. on p. 2).

Frestad, Dennis, Fred Espen Benth, and Steen Koekebakker (2010). “Modeling term structure dynamics in the Nordic electricity swap market”. In: *The Energy Journal* 31.2 (cit. on p. 2).

González, Javier Serrano and César Álvarez Alonso (2021). “Industrial electricity prices in Spain: A discussion in the context of the European internal energy market”. In: *Energy Policy* 148, p. 111930 (cit. on p. 2).

Ihlemann, Maren et al. (2022). “Benefits of regional coordination of balancing capacity markets in future European electricity markets”. In: *Applied Energy* 314, p. 118874. ISSN: 0306-2619. DOI: `10.1016/j.apenergy.2022.118874`. URL: `http://dx.doi.org/10.1016/j.apenergy.2022.118874` (cit. on p. 2).

Kemper, Annika, Maren Diane Schmeck, and Anna Kh.Balci (2022). “The market price of risk for delivery periods: Pricing swaps and options in electricity markets”. In: *Energy Economics* 113, p. 106221. ISSN: 0140-9883. DOI: `10.1016/j.eneco.2022.106221`. URL: `http://dx.doi.org/10.1016/j.eneco.2022.106221` (cit. on p. 2).

Lai, Shuying et al. (2021). “Risk hedging for gas power generation considering power-to-gas energy storage in three different electricity markets”. In: *Applied Energy* 291, p. 116822 (cit. on p. 2).

Martin, Robert Andrew (2021). “PyPortfolioOpt: portfolio optimization in Python”. In: *Journal of Open Source Software* 6.61, p. 3066. DOI: `10.21105/joss.03066`. URL: `https://doi.org/10.21105/joss.03066` (cit. on p. 6).

Nazar, Mehrdad Setayesh et al. (2018). “Hybrid model using three-stage algorithm for simultaneous load and price forecasting”. In: *Electric Power Systems Research* 165, pp. 214–228 (cit. on p. 1).

Peña, Juan Ignacio, Rosa Rodríguez, and Silvia Mayoral (2020). “Tail risk of electricity futures”. In: *Energy Economics* 91, p. 104886 (cit. on p. 2).

Zeynali, Saeed et al. (2021). "A hybrid robust-stochastic framework for strategic scheduling of integrated wind farm and plug-in hybrid electric vehicle fleets". In: *Applied Energy* 300, p. 117432. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2021.117432. URL: http://dx.doi.org/10.1016/j.apenergy.2021.117432 (cit. on p. 2).