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Information in Electricity Forward Prices

Richard A. Michelfelder and Eugene A. Pilotte*

Abstract

We examine forward prices in a market where nonstorable inventory exacerbates the influence of seasonal and hourly variation in supply and demand, expected and unexpected, on the level and volatility of spot prices. We find strong evidence, unusual for a commodity, that the difference between contemporaneous forward and spot prices has power to forecast both the spot price change and the risk premium realized at delivery. Our evidence of a time-varying risk premium is consistent with expected hourly and seasonal variation in the needs of producers and retailers of electricity to hedge against extreme spot price decreases and increases, respectively.

I. Introduction

We examine the information content of forward prices in a unique market, the wholesale market for electricity. Electricity is a fascinating commodity to study because it is not cost effectively stored and must be consumed as it is produced. Absent inventories to smooth supply and demand shocks, market-clearing prices are highly volatile. Marginal production costs increase rapidly as production levels approach capacity, producing sudden temporary price spikes. Negative prices occur when power producers pay power users to take surplus power rather than incur the costs of shutting down and restarting a facility. The lack of storage produces predictable temporal variation in the price level, the frequency of price spikes, and the frequency of negative prices. Higher average prices and spikes tend to occur during the summer and winter seasons and daytime hours, because the demand for electricity is higher and more variable than during the temperate seasons or overnight hours. Extreme winter and summer weather, combined with the inelastic demand for electricity to meet space heating and cooling needs, often

*Michelfelder, richmich@camden.rutgers.edu; Pilotte (corresponding author), pilotte@camden.rutgers.edu, Rutgers University School of Business. We are especially grateful to Hendrik Bessembinder (the editor) and an anonymous referee for helpful comments and guidance. We also thank Athul Mohan for excellent research assistance and seminar participants at the Jan. 2018 Rutgers Center for Research in Regulated Industries Advanced Workshop in Regulation and Competition and the 2019 Rutgers Center for Research in Regulated Industries Eastern Conference for helpful suggestions and comments.

produces extreme upward price spikes.[1] The largest price on PJM Interconnection LLC (PJM) occurred on Jan. 7, 2014 during a disruption in the polar vortex. The price of $1,819 per megawatt hour (MWh) was a 43-fold increase relative to the spot price of $42/MWh for the same hour the day prior. Zero and negative prices are most frequent during low-demand early morning hours. The minimum price on PJM, −$230.01/MWh at 7:00 on May 24, 2015, was a 44-fold decrease relative to the price of $5.35/MWh at the same hour on the prior day.

An important consequence of the nonstorability of electricity is that the forward price of electricity cannot be linked to the spot price through the cost-of-carry no-arbitrage condition that emanates from Working's (1949) theory of storage. The idea underlying the cost-of-carry relation is that holding inventory is a substitute for forward purchase, so the forward price on a given date for delivery on a future date must equal the spot price plus the costs of financing and storing the inventory less any convenience yield that holding the inventory provides. Because electricity is not stored cost effectively, this strategy cannot be implemented.

Our article is based on the alternative view that the forward price consists of the sum of a spot price forecast and a risk premium. Keynes (1930) and Cootner (1960) argue that the risk premium represents the fee that hedgers of price risk pay speculators to assume that risk. If hedgers are sellers seeking insurance against an unexpected price decline, they are willing to compensate speculators by accepting a forward price that is lower than the spot price expected on the delivery date. If hedgers are purchasers, they are willing to pay a forward price that exceeds the expected spot price. Thus, the size and sign of the risk premium is determined by "hedging pressure," the extent to which hedgers are net short or net long. Evidence of the influence hedging pressure has on forward (futures) prices is provided by Carter, Rausser, and Schmitz (1983), Chang (1985), Bessembinder (1992), De Roon, Nijman, and Veld (2000), and Acharya, Lochstoer, and Ramadorai (2013). Bessembinder and Lemmon (2002) present an equilibrium model of the electricity market that implies that the forward risk premium varies in magnitude and sign with the hedging needs of producers and retailers of wholesale power.

The risk premium is important because it represents the cost of hedging and compensation for risk bearing, and because it is the bias in the forward price as a forecast of the expected spot price. Economic decision makers who look at forward prices as indicators of future spot prices need to understand the nature of the bias to extract the spot price forecast. The nonstorability of electricity combined with predictable temporal variation in electricity demand and demand variability suggest substantial temporal variation in expected spot price changes and ex ante risk premiums that should be reflected in forward prices. During the seasons and hours associated with high demand, high price volatility, and price spikes, a heightened need for electricity retailers to hedge the cost of electricity purchases is likely to produce positive forward premiums. During the seasons and hours associated with low demand and sharp downward price moves that may lead to

[1] The demand for electricity at the margin is mainly weather driven by the demand for space heating or cooling and is not very responsive to price. Supply at the margin is also price inelastic, because there are limits on how quickly traditional power-generation sources can be ramped up or down in production and because renewables (solar, wind, and hydro) are dispatched by weather.

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negative prices, a heightened need for producers to hedge revenue and the costs of shutting down facilities is likely to produce negative forward premiums. For the power markets examined in this article, temporal variation in hedging pressure is more likely to produce positive risk premiums during the summer and winter seasons and daytime hours, and negative risk premiums during the temperate seasons and early morning hours. Similarly, expected spot price changes are more likely to be positive during periods of increasing demand and negative during periods of decreasing demand. Previously reported seasonal variation in average daily spot prices and average realized risk premiums (see, e.g., Bessembinder and Lemmon (2002)) suggest substantial variation in both spot price forecasts and ex ante risk premiums, making the dominant source of variation in forward prices difficult to predict. Reported hourly variation in average spot prices and average risk premiums (e.g., Longstaff and Wang (2004)) suggests that the relative contributions of the two components of forward prices may change by hour of the day. Although nonstorability should contribute to predictable variation in spot price changes and realized risk premiums, it also exacerbates the impact on prices and premiums of unexpected shocks to demand and supply. The resulting random noise may preclude statistically reliable evidence of the information content in forward prices (see, e.g., Fama and French (1987), Bessembinder and Lemmon (2002)). The usefulness and relative contributions of the predictions embedded in forward prices in predicting realized price changes and risk premiums across seasons and hours of the day are ultimately an empirical issue and the primary focus of this article.

We jointly measure the information contained in day-ahead forward electricity prices about time-varying risk premiums and future spot prices using the approach that Fama and French (1987) use to examine a variety of commodity futures prices (not including energy). For our primary data source, PJM, we find that the basis (i.e., the difference between the forward price for delivery of electricity during a specified hour of the next day and the spot price for delivery during that specified hour on the current day) has power to predict both the day-to-day change in the spot price for that hour and the risk premium realized at delivery. Results for each hour of the day, season of the year, and subperiod support two general conclusions. First, variation in the basis is attributable to variation in both an expected spot price change and an ex ante risk premium. Second, the predominant source of variation in the basis is variation in the expected spot price change. Moreover, we find evidence of hourly and seasonal variation in the relative contributions of the expected spot price change and the ex ante risk premium to variation in the basis that is consistent with expected temporal variation in the hedging needs of generators and retailers of electricity. The contribution of the ex ante premium is greater during on-peak demand hours than during off-peak demand hours and greater during the winter and summer months when demand for power is high and highly variable than during other months. Our examination of the time stability of regression estimates shows that the relative contribution of the risk premium declines during some (mostly off-peak) hours and increases during some other (mostly on-peak) hours. Evidence that time-varying risk premiums persist in the mature PJM market supports the conclusion that risk premiums represent rewards for economic risk rather than a lack of market learning or efficiency. We find

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similar results for the less mature independent system operator (ISO) markets of New England (ISO-NE) and New York (NYISO).

Our evidence that the Fama and French (1987) regressions have substantial power to reveal the information in forward electricity prices contrasts with their findings for 21 other commodities. They find evidence of time-varying risk premiums for 5 commodities, evidence of time-varying spot price forecasts for 10 commodities and evidence of both for only 2 commodities. We attribute our stronger results for electricity to the combination of nonstorability and predictable variation in demand and demand variability producing substantial temporal variation in expected spot prices and ex ante risk premiums. Gorton and Rouwenhorst (2006), Gorton, Hayashi, and Rouwenhorst (2012), and Bhardwaj, Gorton, and Rouwenhorst (2016) examine the returns to investment in commodity futures as a class, forming portfolios to reduce the noise inherent in individual commodity data. They find evidence of normal backwardation, where long investors in commodity futures earn a positive risk premium because hedgers are typically net short, seeking insurance against decreases in future spot prices. We attribute our strong evidence of a risk premium of varying sign to the nonstorability of electricity exacerbating temporal variation in the needs for producers and retailers to hedge against spot price decreases and increases, respectively. Evidence consistent with this interpretation is Gorton et al.'s (2012) finding that the risk premium to long investors in futures on storable commodities declines with the scarcity of inventory.

Studies of electricity markets relate the ex post forward premium to the upward spot price spikes that produce extreme positive skewness in the statistical distribution of spot prices. The Bessembinder and Lemmon (2002) model implies time-varying forward premiums that are negatively related to the variance and positively related to the skewness of spot prices. They also find some empirical evidence that 1-month forward premiums on PJM are positive in the summer and winter months associated with highly variable demand and spot price spikes, and near zero or negative in the fall and spring. Longstaff and Wang (2004) find that hourly averages of premiums for PJM day-ahead forward contracts are negatively related to the hourly variance and positively related to the hourly skewness of the spot price. They also find, for some hours of the day, that realized forward premiums are significantly related to measures of economic risks faced by market participants. Douglas and Popova (2008), Viehmann (2011), and Lucia and Torró (2011) find that ex post risk premiums are significantly related to variables indicating the risk of price spikes.[2] Haugom and Ullrich (2012) find that rolling regressions of PJM risk premiums on spot price skewness and variance produce coefficients that are unstable and of varying sign. They also find that the forward price is an unconditionally and conditionally unbiased forecast of the expected spot price, but do not consider the information in the basis.

Other papers fit continuous-time models to spot and forward electricity prices. Cartea and Villaplana (2008) and Pirrong and Jermakyan (2008) assume

[2]The variables are natural gas inventories during high-demand summer months for PJM, the tightness of the German power system, and reservoir levels on the Nordic Power exchange, respectively.

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that electricity prices are explained by observable state variables.[3] Diko, Lawford, and Limpens (2006), Kolos and Ronn (2008), and Xiao, Colwell, and Bhar (2015) rely on price dynamics alone. Although these studies vary in terms of markets examined and contract specifics, they support the conclusion that variation in one or more market prices of risk produce positive forward premiums during seasons when spot prices typically exhibit high volatility and positive skewness.[4] Other papers propose stochastic models of spot electricity prices that incorporate spike, seasonal, and mean-reverting components.[5]

Motivated by the high frequency of negative German intraday prices on the European Energy Exchange (EPEX), recent studies incorporate the risks of downward price spikes and negative spot prices. Fanone, Gamba, and Prokopczuk (2013) provide a non-Gaussian model that can generate extreme positive and negative price spikes, and find that incorporating negative prices and spikes is necessary for a good fit of the first 4 moments of German electricity spot prices. Paraschiv, Erni, and Pietsch (2014), De Vos (2015), Hagfors, Paraschiv, Molnar, and Westgaard (2016), and Valitov (2019) provide empirical evidence that links the high incidence of negative prices on the EPEX to the increasing use of electricity production from renewable sources after the German Renewable Energy Act. That evidence attributes negative prices to higher than expected energy production from renewables during nighttime hours of low demand and positive spikes to lower than expected production during daytime hours of high demand. Although most frequent in Germany, *Bloomberg* reports that the incidence of negative prices is increasing in many markets because the growing amount of power produced by renewable sources varies with weather conditions rather than demand.[6] We find that the basis has power to forecast spot price changes and risk premiums in three markets that differ in their reliance on renewable sources.

Common to the aforementioned studies of electricity markets is a focus on modeling price spikes and/or relating forward risk premiums to the risk of price spikes. Because each study focuses on a specific market, empirical specifications are generally market specific. Though Bessembinder and Lemmon (2002) offer an empirical specification that expresses the forward premium as a linear function of the variance and skewness of spot prices, that specification has not produced consistent results across markets or in individual markets over time. Thus, the

[3]In Cartea and Villaplana (2008), prices are a function of demand (load) and generation capacity. Pirrong and Jermakyan (2008) use load and fuel price.

[4]Diko et al. (2006) use the EPEX, France Powernext, and the Amsterdam Power Exchange. Pirrong and Jermakyan (2008) and Xiao et al. (2015) focus exclusively on PJM. Kolos and Ronn (2008) use PJM, Cinergy, and the EPEX. Cartea and Villaplana (2008) use PJM, the Nord Pool, and the England and Wales Power Pool.

[5]Spikes in the price process are introduced by introducing jumps into Gaussian diffusion processes by Cartea and Figueroa (2005), Knittel and Roberts (2005), and Seifert and Uhrig-Homburg (2007). Regime-switching processes are used in Geman and Roncoroni (2006), Huisman and Mahieu (2003), De Jong (2006), Weron (2009), and Bierbrauer, Menn, Rachev, and Trück (2007). Models based on Levy jump diffusions are proposed by Benth, Kallsen, and Meyer-Brandis (2007), Meyer-Brandis and Tankov (2008), Klüppelberg, Meyer-Brandis, and Schmidt (2010), and Borovkova, Permana, and Pavlyukevich (2009).

[6]See Starn, J. "Power Worth Less Than Zero Spreads as Green Energy Floods the Grid." *Bloomberg* (Aug. 5, 2018), https://www.bloomberg.com/news/articles/2018-08-06/negative-prices-in-power-market-as-wind-solar-cut-electricity.

literature lacks a unifying framework for predicting the risk premium. Our evidence that the basis has power to predict spot price changes and risk premiums each hour of the day and season of the year in three power markets, along with the stability of our empirical estimates over time, suggests that greater reliance on the basis has the potential to better relate predictability, risk, and return across electricity markets. The basis is effectively Koijen, Moskowitz, Pedersen, and Vrugt's (2018) concept of carry, an asset's futures return assuming that prices stay the same, which they argue provides a unifying framework for return predictability and find has predictive power for many asset classes. Thus, the basis has the potential to relate electricity markets to a broad set of markets.

II. Regression Model and Methodology

We apply the regression approach that Fama (1984a), (1984b) and Fama and French (1987) use to examine forward exchange rates, forward rates on U.S. Treasury bills, and commodity futures prices (energy excluded), respectively. Fama (1984a) discusses the regressions and their interpretation in great detail, so we limit our discussion to the salient points.

The forward price $F_{t,t+1}$ quoted on day t for delivery of 1 MWh of electricity during a specified hour on day $t+1$, can be expressed as the sum of a price forecast and a risk premium:

$$F_{t,t+1} = E_t(S_{t+1}) + P_{t,t+1} \tag{1}$$

where S_{t+1} is the spot (real-time) price for delivery during the same hour on day $t+1$, $E_t(S_{t+1})$ is the market's day t rational expectation of S_{t+1}, and $P_{t,t+1}$ is the ex ante forward risk premium. The basis is the difference between the forward price and the spot price observed on day t:

$$F_{t,t+1} - S_t = E_t(S_{t+1} - S_t) + P_{t,t+1}. \tag{2}$$

Therefore, the basis contains the market's forecast of the expected change in the spot price $E_t(S_{t+1} - S_t)$ and the ex ante risk premium $P_{t,t+1}$. The complementary regression equations are:

$$S_{t+1} - S_t = \propto_{\Delta S} + \beta_{\Delta S}(F_{t,t+1} - S_t) + \varepsilon_{\Delta S,t+1}, \tag{3}$$

$$F_{t,t+1} - S_{t+1} = \propto_P + \beta_P(F_{t,t+1} - S_t) + \varepsilon_{P,t+1}. \tag{4}$$

Assuming that the spot and forward forecasts are efficient or rational, regressions (3) and (4) reveal whether the basis has power to predict the day-to-day change in the spot price and the realized risk premium, respectively. The difference between $\beta_{\Delta S}$ and β_P is an estimate of the relative contributions of the variances of $E_t(S_{t+1} - S_t)$ and $P_{t,t+1}$ to the variance in $F_{t,t+1} - S_t$:

$$\beta_{\Delta S} - \beta_P = \frac{\sigma^2\{E_t(S_{t+1} - S_t)\} - \sigma^2\{P_{t,t+1}\}}{\sigma^2\{F_{t,t+1} - S_t\}}, \tag{5}$$

where $\sigma^2\{\cdot\}$ denotes the variance operator. If $\beta_{\Delta S} - \beta_P$ is positive (negative), the variance of the expected spot change is greater (less) than the variance of the expected premium.

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Because the dependent variables in regression equations (3) and (4) sum to the basis, the intercepts of the regressions must sum to 0, the slopes to 1.0, and the error terms to 0 period by period. Though the estimates for each regression can be extracted from those of the other, their joint analysis makes clear the information that each contains.

Results that Fama and French (1987) report for commodities other than electricity suggest what we might expect from estimating regressions (3) and (4) in electricity markets. Fama and French find that evidence of forecast power for spot price changes is strongest for commodities (animal and some agricultural products) for which storage costs are high relative to value and there is seasonal variation in the basis. By both standards, the basis in electricity markets should have substantial power to forecast spot price changes. Fama and French find weaker evidence of forecast power for realized risk premiums, but predictive power is better when variation in the basis is substantial relative to variation in the forecasted variable. Our descriptive statistics confirm such variation in our data; therefore, prospects of finding predictable variation in both the spot price change and the realized premium are good.

We estimate regressions (3) and (4) for each of the 24 hours in a day and for on- and off-peak averages as systems using the seemingly unrelated regression (SUR) of Zellner (1962). SUR accounts for heteroscedasticity and improves efficiency by accounting for cross-equation correlations of the error terms due to the intraday overlapping nature of the premiums and spot price changes. To account for serial correlation, we use the Cochrane and Orcutt (1949) procedure to transform the data before performing SUR estimation. Because of the frequency and extremity of outliers in our data, we check that the SUR results are not sensitive to outliers using the robust estimation techniques of Koenker and Bassett (1978) and Yohai (1987).

III. PJM Markets and Data

A. PJM Real-Time and Day-Ahead Markets

PJM is a regional transmission organization (RTO) that operates one of the largest, centrally dispatched, competitive wholesale electric power markets in the world.[7] On Apr. 1, 1997, PJM launched the first bid-based real-time (spot) electricity market and introduced the concept of locational marginal price (LMP), now used in electricity markets around the world. LMP in the real-time market tells market participants the marginal cost to serve the next MWh of load at a specific node (location) on the power grid, taking into account any congestion

[7] As of Dec. 31, 2016, PJM had 986 members including market buyers, sellers, and traders of electricity. PJM's service region includes more than 65 million people in 13 states and the District of Columbia, and accounts for more than 20% of U.S. gross domestic product. PJM also coordinates and directs the operation of the transmission grid and plans improvements to maintain grid reliability. For more background, see the 2016 State of the Market Report for PJM, by Monitoring Analytics LLC (http://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2016.shtml).

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that limits the flow of electricity between sending and receiving nodes.[8] On June 1, 2000, PJM launched the day-ahead electricity market that functions as a standard forward market in which market participants can hedge against price risk by purchasing or selling electricity for delivery any hour of the next day.[9]

We collect hourly real-time and day-ahead prices from the PJM website (https://www.pjm.com). Like Longstaff and Wang (2004), we average LMPs across nodes for each hour of each day to get hourly average prices that are representative of the market-clearing price across the PJM region. There are 24 hourly average spot prices and 24 hourly forward prices for each of 6,011 calendar days from June 1, 2000 to Nov. 14, 2016.

B. Statistical Properties of Hourly Data

We document properties of hourly spot and forward prices and the regression variables derived from those data. The independent regression variable is the basis, observed the day prior for the contract delivered during the specified hour. The dependent regression variables are the forward premium realized on the contract delivered at the specified hour and the day-to-day change in the spot price realized at that specified hour. We also examine daily averages for on- and off-peak hours, to compactly present tendencies shared by some hours of the day and because on- and off-peak averages are used in the settlement of PJM futures contracts traded on the New York Mercantile Exchange (NYMEX). Because of the negative and 0 prices in PJM data, we do not convert our derived series to returns by taking differences in log prices. Using differences in raw prices enables us to incorporate all available price information in our analysis and to avoid truncating the left tail of the spot price distribution.[10]

Figure 1 illustrates seasonal and intraday variation in PJM spot prices with graphs of 30-day moving averages for on- and off-peak hour daily averages. The vertical shading indicates the summer months of June, July, and August. The middle of the unshaded areas represents the winter months of December, January, and February. The graphs show that higher average prices occur during on peak than off peak and that each average tends to spike upward during winter and summer. The magnitude of summer peaks has declined since 2008, whereas the two most predominant winter peaks occurred in 2014 and 2015.

Table 1 reports descriptive statistics for on- and off-peak daily averages. The mean spot price is \$47.27/MWh on peak and \$28.42/MWh off peak. The medians are lower, \$41.37/MWh on peak and \$25.85/MWh off peak. Mean and median

[8]There are approximately 11,000 nodes on the transmission system with separate congestion-based prices for every hour. For more information on LMPs access, see the PJM Learning Center on the PJM website (https://learn.pjm.com/three-priorities/buying-and-selling-energy/lmp.aspx).

[9]Before Mar. 31, 2016, PJM evaluated participants' bids and offers and announced the day-ahead results (24 hourly clearing prices for next-day delivery) by 16:00. Effective Mar. 31, 2016, the posting of day-ahead results was moved to 13:30. This change was made when the Federal Energy Regulatory Commission asked ISOs and RTOs to adjust the time at which results of their day-ahead markets are posted, to allow gas-fired generators sufficient time to procure natural gas supply and pipeline transportation.

[10]To check the influence of the log transformation and resulting exclusion of 0 and negative prices, we estimate but do not report results for our baseline regressions (3) and (4) using log prices. We find no systematic or material changes in coefficient estimates that would cause us to alter our conclusions.

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FIGURE 1

30-Day Moving Averages for Daily On-Peak and Off-Peak Average Spot Prices on PJM

In Figure 1, on-peak hours are the 16 hours ending from 8:00 to 23:00. Off-peak hours are the 8 hours ending from 24:00 to 7:00. For each day, the average price in U.S. dollars (USD) is calculated over on-peak hours and off-peak hours. The 30-day moving averages are averages of the daily on- and off-peak averages for PJM Interconnection LLC (PJM). The vertical shading indicates the summer months of June, July, and August. Prices are dollars per megawatt hour.

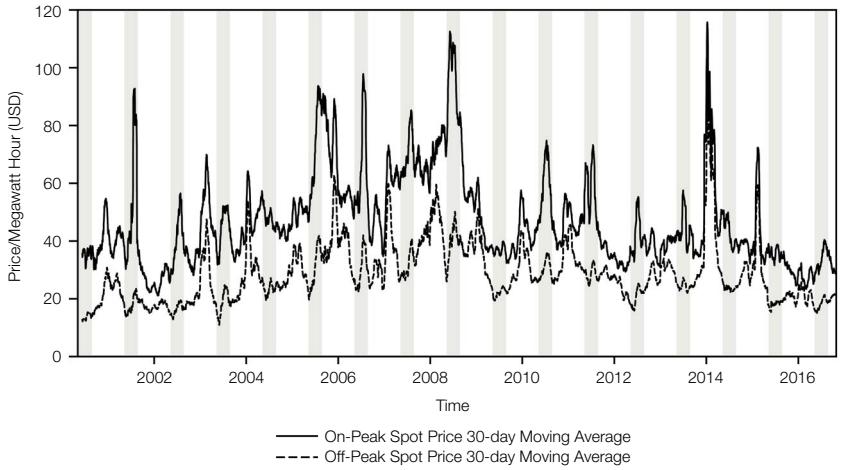


TABLE 1

Descriptive Statistics for On-Peak and Off-Peak Hours

Table 1 provides summary statistics for the daily averages of on-peak and off-peak hourly spot prices and forward prices (for next-day delivery), as reported by PJM Interconnection LLC (PJM) from June 1, 2000 to Nov. 14, 2016. Prices are dollars per megawatt hour. Summary statistics for three series derived from those prices are reported as well. The basis is the difference between the forward price for delivery of electricity during a specified hour of the next day and the spot price for delivery during that specified hour on the current day. The premium is the difference between the forward price for delivery during a specified hour of the next day and the spot price observed during that specified hour on the next day. The spot change is the daily change in the reported spot price for a given hour of the day. Peak hours are the 16 hours ending between 8:00 and 23:00. Off-peak hours are the remaining 8 hours of the day. Low outliers are observations with values below Q1 − 1.5(IQR) and high outliers are above Q3 + 1.5(IQR), where Q1 and Q3 are the upper boundaries of the first and third quartiles, respectively, and IQR is interquartile range. *** indicates statistical significance at the 0.001 level. There are 6,011 observations for each variable.

	On-Peak Hour Daily Average					Off-Peak Hour Daily Average				
Variable	Spot	Forward	Basis	Premium	ΔSpot	Spot	Forward	Basis	Premium	ΔSpot
Mean	47.27***	47.50***	0.23	0.23	0.00	28.42***	28.58***	0.16	0.15	0.00
Std. dev.	26.31	23.84	15.46	20.68	21.10	16.64	14.06	9.33	11.84	13.94
Skewness	6.78	5.94	−2.15	−3.63	−2.47	7.06	6.10	−2.89	−7.27	0.52
Kurtosis	131.62	99.20	363.51	245.23	233.83	123.14	92.08	243.29	265.27	182.52
Minimum	12.74	14.60	−510.49	−649.54	−644.27	−30.89	3.37	−247.11	−395.67	−300.84
Q1	32.38	34.00	−4.06	−6.00	−6.92	19.94	20.97	−1.83	−2.92	−3.62
Median	41.37***	42.12***	1.41***	1.59***	−0.49	25.85***	26.43***	0.56***	0.57***	−0.05
Q3	55.32	54.66	5.31	7.30	6.86	32.57	32.79	2.87	3.93	3.84
Maximum	770.20	655.99	471.93	504.58	519.84	442.67	332.02	236.02	179.02	376.79
IQR	22.94	20.66	9.37	13.30	13.78	12.63	11.82	4.70	6.85	7.46
% < Q1 − 1.5(IQR)	0.00%	0.00%	4.79%	4.61%	3.19%	0.17%	0.00%	5.76%	5.01%	4.67%
% > Q3 + 1.5(IQR)	5.11%	5.09%	2.78%	3.01%	3.83%	5.27%	4.46%	3.96%	3.48%	4.38%
% of averages ≤ 0	0.00%	0.00%				0.18%	0.00%			
% of hours ≤ 0	0.05%	0.00%				1.46%	0.02%			

forward prices are similar to those for spot prices. The means for the basis and the realized premium are positive and higher on peak than off peak, but do not differ significantly from 0. The medians for the basis and the premium are larger

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than the corresponding means and do differ significantly from 0. The significant median forward premiums support the conclusion that more often than not, sellers of day-ahead forward contracts earn a positive premium at the expense of buyers seeking insurance against unexpected increases in the cost of wholesale power. This finding is contrary to the often-made assumption that hedgers in commodity futures markets are predominately commodity sellers. Means and medians for the day-to-day change in the spot price are close to 0 during both on- and off-peak hours. The standard deviations, interquartile ranges (IQRs), minimums, and maximums for each variable document greater volatility on peak than off peak. Spot and forward prices are positively skewed, whereas the derived data series are negatively skewed. All of the data series are leptokurtic (fat-tailed). Jarque–Bera statistics (not tabulated) reject the null that data are normally distributed at confidence levels below 0.001.

Table 1 also reports the percent frequencies of observations classified as outliers. Low outliers are observations with values below Q1 − 1.5(IQR) and high outliers are above Q3 + 1.5(IQR), where Q1 and Q3 are the upper boundaries of the first and third quartiles, respectively. Few observations should be classified as outliers for a variable generated by most standard statistical distributions. For example, a normally distributed random variable is expected to have 0.35% of observations in each outlier category. A comparison of standard deviations, IQRs, and outlier frequencies indicates that the distributions for derived series are more symmetric than those for spot and forward prices. The outlier frequencies suggest that the potential for extreme values to influence parametric statistics is high. For spot and forward price daily averages, both on peak and off peak, approximately 5% of observations are high outliers, whereas low outliers are few. For the basis, premium, and change in spot price, the combined frequency of low and high outliers varies from 7.02% for the on-peak price change to 9.72% for the off-peak basis. The high frequency of outliers and negative skewness explain why the medians, but not the means, are positive and significant for the premium and basis. The distributional properties of our data indicate the importance of robustness checks when employing parametric methods to analyze price data from electricity markets, as data are not normally distributed and outliers are pervasive.

Table 1 reports the frequencies of on- and off-peak hour spot and forward prices that are less than or equal to 0. Nonpositive spot prices are concentrated during off-peak hours, with a frequency of 1.46%. Nonpositive forward prices are rare. Daily averages are rarely nonpositive, comprising 0.18% of the off-peak daily average spot price.

We examine, but do not tabulate, descriptive statistics for each hour of the day. For each hour, each series is skewed and leptokurtic with a large frequency of outliers. As is the case for on- and off-peak averages, the medians for the premium and basis are always significantly greater than 0; the means are of mixed sign and significance. Without the effects of averaging across hours, the range of outlier frequencies is greater for hourly data than for on- and off-peak averages, ranging from 5.19% to 8.05% for spot prices, 3.53% to 7.05% for forward prices, 9.48% to 12.69% for the premium, 11.30% to 14.79% for spot price changes, and 11.84% to 15.01% for the basis. The frequency of nonpositive hourly spot prices is as high as 2.94% at 4:00. The largest average premiums occur during the hour ending at

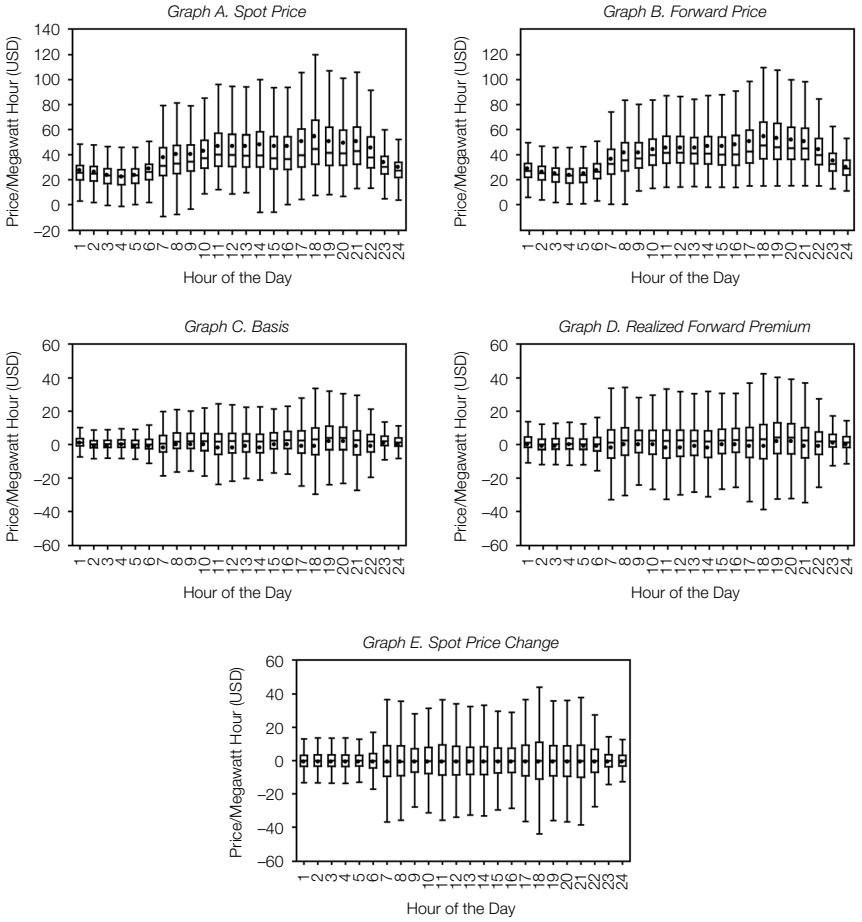
19:00, when the mean premium of $2.46/MWh is approximately 4.7% of the mean spot price for that hour. The median premium of $4.29/MWh is approximately 10.3% of the median spot price during that hour. Our percentage premiums are smaller than those reported by Longstaff and Wang (2004) but still represent a huge average risk premium for bearing spot price risk for 1 day.

Box plots for the hourly data series are shown in Figure 2. Outliers are suppressed to ensure the visibility of intraday variation in the central tendencies. Each box represents observations in the second and third quartiles, the middle of the distribution. The distance between the box boundaries is the IQR. The ends of the "whiskers" extending from the boxes identify the highest and lowest datum

FIGURE 2

Distribution of Hourly Wholesale Electricity Prices on PJM (Outliers Suppressed)

Figure 2 displays boxplots of hourly spot and 1-day-ahead forward prices in U.S. dollars (USD) as reported by PJM Interconnection LLC (PJM) from June 1, 2000 to Nov. 14, 2016, and three series derived from those prices. The basis is the difference between the 1-day-ahead forward price on a given day and the spot price that day. The premium is the difference between the forward price on a given day and the spot price observed at that hour on the next day. The spot price change is the daily change in the reported spot price for a given hour. Prices are dollars per megawatt hour.



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not classified as outliers. The dot in each box represents the mean and the horizontal bar represents the 95% confidence interval for the median; therefore, the medians for which the bars do not overlap differ significantly. The plots for spot prices, forward prices, the basis, and the realized forward premium show medians that are low during early morning off-peak hours and drift upward to their highest levels during the on-peak hours of 18:00 to 21:00. For both the basis and the realized forward premium, the medians are positive and differ significantly from 0, but the means meander around 0. The variation in median realized risk premiums across hours of the day supports the conclusion that more often than not, sellers of day-ahead forward contracts earn a positive risk premium from buyers that is small during early morning hours and increases to high levels during the hours associated with extreme upward price movements. For the day-to-day change in the spot price, both means and medians are close to 0 throughout the day. Each derived series exhibits lower dispersion during off-peak hours than during on-peak hours.

IV. Regression Results for PJM

In this section, we test the predictive power of the basis, test for seasonal differences, and examine the time stability and robustness of our results.

A. Full-Sample Results for Base Regressions

In Table 2, we report results of estimating regressions (3) and (4). Four results are consistent for off- and on-peak hour daily averages and for each hour of the day. First, estimates of $\beta_{\Delta S}$ are always positive and statistically different from 0 at the 0.001 level, providing evidence that the basis has predictive power for the average daily changes in on- and off-peak hour spot prices, as well as for the day-to-day change in the spot price for every hour of the day. Second, estimates of β_P, though of smaller magnitude than estimates of $\beta_{\Delta S}$, are also consistently positive and statistically different from 0 at the 0.001 level, providing evidence that the basis has predictive power for the 1-day risk premium realized at the delivery hour. Third, estimates of the difference, $\beta_{\Delta S} - \beta_P$, are always positive and statistically different from 0 at the 0.001 level, providing evidence that the variance of the expected change in the spot price, $E_t(S_{t+1} - S_t)$, is always greater than the variance of the ex ante premium, $P_{t,t+1}$. Fourth, for every regression pair, the R^2 is higher for the spot price change regression, indicating that the basis explains a greater proportion of variation in the spot price change than does the premium.

In comparing the slope estimates for off- and on-peak averages, the contribution of the expected spot price change to variation in the basis is greater off peak than on peak, whereas the risk premium contribution is greater on peak than off peak. Similarly, the R^2 for the spot change regression is larger off peak than on peak, whereas the R^2 for the premium regression is greater on peak than off peak. The differences, $\beta_{\Delta S} - \beta_P$, indicate that although the contribution of the risk premium to variation in the basis is higher during the on-peak period, the variance of the expected spot change is always greater than the variance of the premium. Results for individual hours indicate that the contribution of the expected spot

TABLE 2

Regressions of Change in Spot Price and Realized Premium on the Basis

Table 2 presents regression estimates of the following equations:

$$S_{t+1} - S_t = \alpha_{\Delta S} + \beta_{\Delta S}(F_{t,t+1} - S_t) + \varepsilon_{\Delta S,t+1},$$
$$F_{t,t+1} - S_{t+1} = \alpha_P + \beta_P(F_{t,t+1} - S_t) + \varepsilon_{P,t+1}.$$

The variables for on-peak and off peak regressions are daily averages, for PJM Interconnection LLC (PJM), calculated over on-peak hours (8:00 to 23:00) and off-peak hours (24:00 and 1:00 to 7:00), respectively. The other regressions are based on hourly PJM data. S_t is the spot price observed at the indicated hour on day t. $F_{t,t+1}$ is the forward price observed on day t for delivery at the indicated hour on day $t+1$. Prices are dollars per megawatt hour. For both specified regressions, hourly regressions are estimated as a system using seemingly unrelated regression estimation after a Cochrane–Orcutt transformation to adjust for serial correlation. On-peak and off-peak regressions are also estimated as a system. Standard errors of coefficients and their differences are denoted SE (·). *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 levels, respectively.

Hours	$\alpha_{\Delta S}$	$\beta_{\Delta S}$	α_P	β_P	SE (α)	SE (β)	$\beta_{\Delta S} - \beta_P$	SE ($\beta_{\Delta S} - \beta_P$)	$R^2_{\Delta S}$	R^2_P
Off peak	−0.12	0.80***	0.12	0.20***	0.15	0.01	0.60***	0.03	0.30	0.02
On peak	−0.15	0.65***	0.15	0.35***	0.25	0.01	0.31***	0.03	0.14	0.11
1:00	−0.92***	0.77***	0.92***	0.23***	0.15	0.01	0.53***	0.02	0.25	0.06
2:00	0.42*	0.95***	−0.42*	0.05***	0.17	0.01	0.90***	0.02	0.39	0.00
3:00	−0.16	0.93***	0.16	0.07***	0.16	0.01	0.87***	0.02	0.37	0.00
4:00	−0.57***	0.95***	0.57***	0.05***	0.16	0.01	0.89***	0.02	0.38	0.00
5:00	−0.18	0.94***	0.18	0.06***	0.16	0.01	0.89***	0.02	0.38	0.00
6:00	0.20	0.87***	−0.20	0.13***	0.24	0.01	0.74***	0.02	0.39	0.00
7:00	1.00**	0.83***	−1.00**	0.17***	0.35	0.01	0.65***	0.02	0.32	0.02
8:00	−0.41	0.80***	0.41	0.20***	0.41	0.01	0.60***	0.02	0.17	0.03
9:00	−0.88*	0.77***	0.88*	0.23***	0.35	0.01	0.53***	0.01	0.30	0.05
10:00	−0.17	0.81***	0.17	0.19***	0.36	0.01	0.62***	0.01	0.32	0.04
11:00	1.15**	0.84***	−1.15**	0.16***	0.37	0.01	0.69***	0.02	0.34	0.02
12:00	0.69*	0.84***	−0.69*	0.16***	0.35	0.01	0.69***	0.02	0.34	0.02
13:00	0.62*	0.84***	−0.62*	0.16***	0.31	0.01	0.68***	0.02	0.29	0.04
14:00	1.35***	0.89***	−1.35***	0.11***	0.35	0.01	0.77***	0.02	0.27	0.03
15:00	−0.26	0.93***	0.26	0.07***	0.37	0.01	0.85***	0.02	0.21	0.02
16:00	−0.72	0.89***	0.72	0.11***	0.42	0.01	0.78***	0.02	0.25	0.04
17:00	0.12	0.90***	−0.12	0.10***	0.43	0.01	0.81***	0.02	0.23	0.04
18:00	0.27	0.93***	−0.27	0.07***	0.44	0.01	0.85***	0.02	0.27	0.02
19:00	−1.69***	0.72***	1.69***	0.28***	0.36	0.01	0.44***	0.02	0.17	0.12
20:00	−1.44***	0.68***	1.44***	0.32***	0.34	0.01	0.37***	0.02	0.17	0.13
21:00	0.63	0.79***	−0.63	0.21***	0.35	0.01	0.59***	0.02	0.27	0.05
22:00	0.55*	0.77***	−0.55*	0.23***	0.25	0.01	0.55***	0.02	0.22	0.08
23:00	−1.08***	0.63***	1.08***	0.37***	0.17	0.01	0.25***	0.02	0.12	0.17
24:00	−0.75***	0.78***	0.75***	0.22***	0.16	0.01	0.56***	0.02	0.25	0.07

change to variation in the basis is highest during the early morning hours ending from 2:00 to 6:00, whereas the contribution of the risk premium is highest during the evening hours ending from 19:00 to 24:00.

Overall, the full-sample results demonstrate that electricity forward prices for each hour of the day contain both a time-varying risk premium and spot price forecast that show up in the ability of the basis to predict realized risk premiums and spot price changes. The fact that both $\beta_{\Delta S}$ and β_P are positive fractions indicates that variation in both the predicted spot price change and the predicted premium are proportional to variation in the basis. The results show that variation in the risk premium is more important during periods of the day that are associated with greater spot price volatility and upward price spikes. The results are consistent with Fama and French (1987) in providing additional evidence that the basis has strong power to predict spot price changes for commodities for which storage costs are high relative to value and that the often-difficult-to-document variation in risk premiums shows up for a commodity for which variation in the basis is substantial relative to variation in the premium.

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B. Regressions and Seasonal Effects

Table 2 results reveal that the relative contribution of the risk premium to variation in the basis is greater during the hours of the day associated with high spot price volatility and upward price spikes. Figure 1 shows that spot price volatility and spike frequency are highest in summer and winter. Therefore, it is reasonable to expect the premium to contribute more during summer and winter than during shoulder seasons. Conversely, because spot prices are more volatile in summer and winter, there are larger price changes to predict and it is possible that the variance of forecasts of spot price changes could increase more than the variance of the risk premium.

We test for seasonal changes in the slope coefficients of the premium regressions by augmenting regression (4) with seasonal dummy variables interacted with the basis. We tabulate only the results of the risk premium regression to conserve space and because the question of a time-varying risk premium is the main focus of the literature. As previously noted, because of the complementarity of the risk premium and spot change regressions, any change in the slope for the risk premium regression must be accompanied by a change of equal magnitude but opposite sign in the slope for the spot change regression. The augmented regression equation is:

$$(6)\quad F_{t,t+1} - S_{t+1} = \propto_P + \beta_P (F_{t,t+1} - S_t) + \beta_S D_{\text{SUMMER}} (F_{t,t+1} - S_t) + \beta_F D_{\text{FALL}} (F_{t,t+1} - S_t) + \beta_W D_{\text{WINTER}} (F_{t,t+1} - S_t) + \varepsilon_{P,t+1}.$$

The dummy variables equal 1 for data for the indicated season, and 0 otherwise. Summer months are June, July, and August; fall months are September, October, and November; and winter months are December, January, and February. The coefficient β_P is the slope coefficient for spring months, and β_S, β_F, and β_W are estimates of the seasonal differences relative to spring.

Table 3 presents the results of estimating regression equation (6). Results for on- and off-peak averages and for individual hours provide evidence that the contribution of the risk premium to variation in the basis varies seasonally, tending higher during the summer and winter months associated with high spot price volatility, price spikes, and increased risk for purchasers of wholesale electricity. For off- and on-peak averages, the estimates of β_P are positive and statistically significant at the 0.001 level, indicating that the risk premium contributes to variation in the basis during both off- and on-peak hours during the spring. The estimates of β_S are positive and significant at the 0.01 level, demonstrating an increase in the relative contribution of the risk premium during the summer off- and on-peak hours. Estimates of β_F are positive but insignificant, indicating that the contribution of the risk premium during the fall does not differ from that during the spring. The estimate of β_W is positive and statistically significant at the 0.001 level for on-peak hours, but insignificant for off-peak hours, indicating an increase in the contribution of the risk premium during winter months only during on-peak hours.

The results for individual hours are largely consistent with those for the off- and on-peak averages. Estimates of β_P are positive and differ significantly from 0 at the 0.05 (or lower) level in 20 of the 24 hourly regressions, indicating

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TABLE 3

Regressions of the Realized Premium of the Basis with Seasonal Interactions

Table 3 presents regression estimates of the following equation:

$$F_{t,t+1} - S_{t+1} = \alpha_P + \beta_P(F_{t,t+1} - S_t) + \beta_S D_{\text{SUMMER}}(F_{t,t+1} - S_t) + \beta_F D_{\text{FALL}}(F_{t,t+1} - S_t) + \beta_W D_{\text{WINTER}}(F_{t,t+1} - S_t) + \varepsilon_{P,t+1}.$$

The variables for on-peak and off-peak regressions are daily averages, for PJM Interconnection LLC (PJM), calculated over on-peak hours (8:00 to 23:00) and off-peak hours (24:00 and 1:00 to 7:00), respectively. The remaining regressions are based on hourly PJM data. S_t is the spot price observed at the indicated hour on day t. $F_{t,t+1}$ is the forward price observed on day t for delivery at the indicated hour on day $t+1$. Prices are dollars per megawatt hour. D_{SUMMER}, D_{FALL}, and D_{WINTER} are dummy variables that identify the season of the year. Summer months are June, July, and August; fall months are September, October, and November; and winter months are December, January, and February. For the regression specified, hourly regressions are estimated as a system using seemingly unrelated regression estimation after a Cochrane–Orcutt transformation to adjust for serial correlation. On-peak and off-peak regressions are also estimated as a system. Standard errors of coefficients are denoted SE (·). *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 levels, respectively.

Hours	α_P	β_P	β_S	β_F	β_W	SE (α_P)	SE (β_P)	SE (β_S)	SE (β_F)	SE (β_W)	R^2_P
Off peak	0.11	0.25***	0.17**	0.06	−0.09	0.15	0.04	0.07	0.07	0.05	0.02
On peak	0.12	0.20***	0.13**	0.04	0.19***	0.25	0.04	0.05	0.06	0.04	0.12
1:00	0.96***	0.17***	0.08*	−0.05	0.09**	0.15	0.03	0.04	0.04	0.03	0.06
2:00	−0.41**	0.04	0.08*	0.00	0.01	0.16	0.02	0.03	0.03	0.02	0.00
3:00	0.18	−0.02	0.11***	0.08*	0.11***	0.16	0.02	0.04	0.04	0.03	0.00
4:00	0.56***	0.06**	0.01	0.01	0.00	0.16	0.02	0.04	0.04	0.03	0.00
5:00	0.17	0.06**	0.06	0.02	0.01	0.16	0.02	0.03	0.04	0.02	0.00
6:00	−0.19	0.07***	0.09*	0.12**	0.09***	0.24	0.02	0.04	0.04	0.02	0.00
7:00	−1.00**	0.12***	0.05	0.03	0.10***	0.35	0.02	0.05	0.04	0.03	0.01
8:00	0.41	0.12***	0.08	0.05	0.12***	0.41	0.02	0.05	0.04	0.02	0.03
9:00	0.86*	0.23***	0.00	−0.02	0.03	0.35	0.02	0.04	0.03	0.02	0.05
10:00	0.16	0.19***	0.00	−0.05	0.03	0.36	0.02	0.03	0.03	0.02	0.04
11:00	−1.14***	0.15***	0.03	−0.01	0.03	0.37	0.02	0.03	0.03	0.02	0.02
12:00	−0.68*	0.09***	0.09***	0.00	0.10***	0.35	0.02	0.03	0.03	0.03	0.02
13:00	−0.66*	0.05*	0.16***	0.01	0.12***	0.31	0.02	0.03	0.04	0.03	0.04
14:00	−1.39***	0.06*	0.07**	0.01	0.11***	0.35	0.02	0.03	0.04	0.03	0.03
15:00	0.20	0.00	0.09**	0.04	0.18***	0.37	0.03	0.03	0.04	0.05	0.03
16:00	0.64	0.12***	−0.03	−0.01	0.14***	0.42	0.02	0.02	0.04	0.04	0.04
17:00	−0.35	0.06**	−0.01	0.04	0.30***	0.43	0.02	0.02	0.03	0.03	0.04
18:00	−0.27	0.02	0.07**	0.07	0.07**	0.44	0.02	0.03	0.04	0.03	0.03
19:00	1.72***	0.20***	0.06	0.08**	0.11***	0.36	0.03	0.04	0.04	0.03	0.12
20:00	1.36***	0.21***	0.16***	0.08**	0.15***	0.34	0.02	0.03	0.03	0.02	0.13
21:00	−0.64	0.12***	0.08**	0.16***	0.11***	0.35	0.02	0.03	0.03	0.03	0.05
22:00	−0.57*	0.18***	0.02	0.04	0.09***	0.25	0.02	0.03	0.04	0.03	0.08
23:00	1.12***	0.24***	0.13***	0.10**	0.18***	0.17	0.02	0.03	0.04	0.02	0.17
24:00	0.74***	0.25***	0.01	0.04	−0.07**	0.16	0.02	0.03	0.04	0.03	0.07

significant variation in the risk premium during most spring hours. Regarding the seasonal comparisons with spring, estimates of β_S, β_F, and β_W provide evidence that the relative contribution of the risk premium to variation in the basis is significantly (0.05 level) higher in 6 fall hours, 12 summer hours, and 17 winter hours. The single contrary result is the β_w estimate, which is negative and significant at 24:00. Overall, the hourly regressions produce evidence of seasonal effects that is stronger in winter, moderate in summer, and weaker in fall. This is not surprising in light of the recent decreasing severity of summer peaks and increasing severity of winter peaks shown in Figure 1. The decline in the severity of summer peaks is likely attributable to major efficiency improvements in space cooling equipment over time, in contrast to limited efficiency improvements in space heating.

C. Tests of Time Stability of Regression Coefficients

Bessembinder and Lemmon (2002) stress the preliminary nature of their results, due to the inexperience of industry participants with new and unique wholesale power markets and the lack of opportunities for outside investors to share in the risks of the power market. They posit that market learning and the development of contracts that allow outside speculators to take positions in power markets

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are likely to cause a decline in the magnitude of forward risk premiums, perhaps to the point where forward prices are unbiased forecasts of expected spot prices. We investigate this possibility in light of major developments in the PJM market since their study.

Key developments in the PJM market include substantial increases in generating capacity as PJM increased its geographic coverage, with especially large increases in installed capacity in early 2002, late 2004, and mid 2005 (Krapels and Flemming (2005)). Subsequent growth has been more stable. A major increase in risk-sharing opportunities occurred in 2003 with the launch by NYMEX of financially settled daily, weekly, and monthly futures based on PJM Western hub real-time LMPs. In Dec. 2008, NYMEX launched additional PJM zone contracts that extended risk management opportunities throughout the competitive retail markets of PJM. Given the aforementioned developments, we view Dec. 31, 2008 as a justifiable date for dividing our sample into maturing and mature market periods.

We test for a change in the slope coefficients of the premium regressions after 2008 by adding to regression (4) a sample-period dummy variable interacted with the basis. Results of our tests for a single structural break, not tabulated to conserve space, show no consistent change across hours of the day in the relative contribution of the risk premium to variation in the basis. The regression that predicts the average off-peak premium provides evidence of a statistically significant (0.001 level) decrease, but the regression for the average on-peak premium provides evidence of a statistically significant (0.01 level) increase. Hourly regressions confirm the tendency for the contribution of the risk premium to decrease during off-peak hours and increase during on-peak hours.[11]

We use recursive estimation to examine further the stability of regression coefficients. Figure 3 shows graphs of recursive slope coefficient estimates and their 95% confidence intervals for the risk premium regression (4) for daily off-peak and daily on-peak average hourly prices. We require 100 observations to estimate the initial regression.

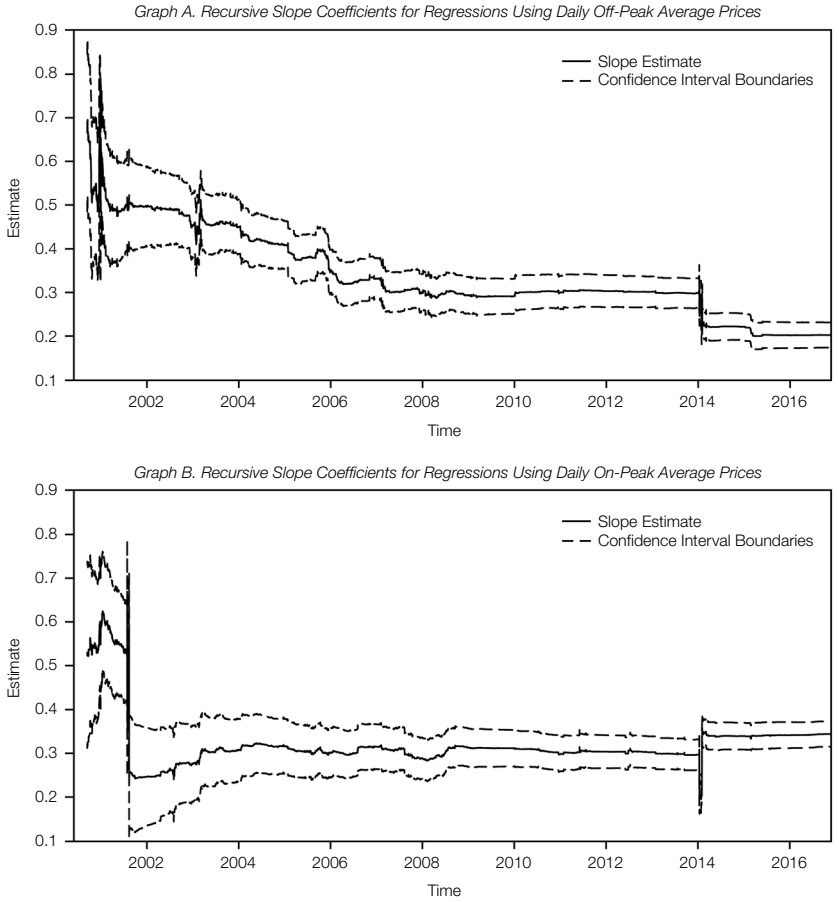
Graph A of Figure 3 shows that the slope coefficients for regressions based on daily average off-peak prices are initially high, decline gradually from early 2001 until early 2008, are stable from 2008 to the end of 2013, and drop sharply in Jan. 2014. Graph B shows that the slope coefficients based on daily average on-peak prices are initially high, drop to a much lower level in the middle of 2001, increase gradually until 2004, are stable from 2004 to the end of 2013, and increase sharply in Jan. 2014. Common to both graphs are the decline in the relative contribution of the risk premium to forward prices in the first year of the day-ahead market, relative stability of that contribution from 2008 through 2013, and sharp change in that contribution in 2014. The difference in the 2 graphs is the time trends after 2001: downward for on-peak prices and upward for off-peak

[11] For hourly regressions, a statistically significant (0.001 level) decrease in the contribution of the premium occurs in 4 of the 8 off-peak hours (4:00, 5:00, 6:00, and 24:00) and 1 on-peak hour (13:00). Statistically significant (0.05 level or lower) increases occur during 6 of the 16 on-peak hours (8:00, 16:00, 17:00, 19:00, 22:00, and 23:00) and 1 off-peak hour (1:00).

FIGURE 3

Recursive Risk Premium Regressions for PJM

Figure 3 illustrates the results of recursive estimation of the risk premium regression for PJM Interconnection LLC (PJM) from June 1, 2000 to Nov. 14, 2016. Graph A displays recursive slope coefficients and 95% confidence intervals for regressions of the daily average of off-peak hour premiums on the daily average of the prior-day off-peak hour basis. Graph B displays results for on-peak hour averages. We require a 100-day minimum to estimate the system.



prices. The opposite shifts in on- and off-peak slope coefficients in Jan. 2014 coincide with the polar vortex disruption during that month.

We conclude that except for the first year of the day-ahead market, there is no decrease over time in the contribution of the risk premium to variation in the basis that is common to all hours of the day. Rather, there is a tendency for the contribution of the risk premium to decrease during off-peak hours and increase during on-peak hours. The tendency during off-peak hours is consistent with the proposed effect of market maturation and increase in risk sharing. The opposite tendency during on-peak hours suggests that there are influences beyond market maturation that affect the evolution of the risk premium. One potential influence is the increasing severity of winter peaks shown in Figure 1. Given the large

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increase in the contribution of the on-peak risk premium during Jan. 2014, it is possible that market participants reassessed the risk of upward price spikes during winter months. Another influence may be differences in the risks that need to be hedged on peak versus off peak, as 0 and negative prices are concentrated in off-peak hours whereas extreme upward price spikes are more frequent during on-peak hours. Both potential influences may be exacerbated by changes over time in the mix of power generation sources, as PJM has retired coal generation facilities and added natural gas and renewables.[12] Greater reliance on natural gas and renewables introduces additional risks into the market, because natural gas is in high demand for space heating during winter months and its delivery may be curtailed due to limits on pipeline capacity, and production from renewable sources is determined solely by weather conditions. Evidence that the mix matters includes the previously cited studies of the impact of wind power in Germany, Lindström and Regland's (2012) evidence that extreme price movements are more frequent in European electricity markets that are more reliant on renewable energy sources, and Huisman and Kilic's (2012) evidence of time-varying risk premiums on monthly contracts in the Dutch market, heavily reliant on natural gas, but not the Nordic market, which relies more on hydropower.

D. Robustness

Our descriptive statistics document the high frequency and extreme nature of outliers in PJM price data and series derived from that data. An obvious concern is that least squares estimates for regression models can be highly sensitive to outliers that produce violations of the assumption of normally distributed residuals. Therefore, we estimate linear models using two methods that are robust to outliers: quantile estimation and robust-MM estimation. The quantile regression technique of Koenker and Bassett (1978) is used to model the conditional median rather than the conditional mean of a dependent variable.[13] The Yohai (1987) robust-MM estimation method is robust to outliers in both dependent and independent variables.

We compare robust regression estimates with those reported in Table 2. Given the similarity of the robust and SUR estimates, we discuss but do not tabulate them. The slope coefficients produced by both robust methods are close to those reported in Table 2 for SUR estimation and to one another. The noticeable tendency is for the robust methods to attribute less of the variance in the basis to the risk premium in the early morning hours ending at 7:00 and 8:00 and more in the late afternoon hours ending from 15:00 to 18:00. All estimates of $\beta_{\Delta S}$ and β_P for the robust-MM method differ significantly from 0 at the 0.001 level. For the quantile regressions, all estimates of $\beta_{\Delta S}$ differ significantly from 0 at the 0.001 level, as do most of the estimates of β_P. The exceptions are the $\beta_{\Delta P}$ estimates

[12] PJM reports that from 2010 to 2016, coal-fired units made up 79% of the megawatts retired, and natural gas and renewables made up 87% of new megawatts placed in service. Whereas coal and nuclear resources provided 91% of the electricity generated on the PJM system in 2005, they represented only 51% of installed capacity in 2016. See "PJM'S Evolving Resource Mix and System Reliability," PJM Interconnection (Mar. 30, 2017), https://www.pjm.com/~/media/library/reports-notices/special-reports/20170330-pjms-evolving-resource-mix-and-system-reliability.ashx.

[13] Hagfors et al. (2016) use quantile regression to address the non-normality of data and regression errors for the EPEX.

for the morning hours ending from 2:00 through 6:00, which are significant at the 0.05 level, and the hours ending at 7:00 and 8:00, which are not statistically significant at the 0.05 level. The estimated differences, $\beta_{\Delta S} - \beta_P$, remain positive and significant at the 0.001 level for every regression pair. Our major conclusions regarding the information content of the basis are insensitive to the choice of SUR system estimation versus single-equation estimation techniques that are robust to frequent, often extreme outliers.

V. Examination of ISO-NE and NYISO

We examine the efficacy of our empirical methods when applied to the NYISO and ISO-NE power pools, which rely more on generation from renewable sources than does PJM. Most notable are the differences in hydroelectric power capacities, which are about 15% of the fuel mix for NYISO, 7% for ISO-NE, and 4% for PJM. Extrapolating from the impact of renewables in Germany, the frequency of negative spot prices should be highest for NYISO and lowest for PJM. The descriptive statistics in Table 4 for on- and off-peak hourly prices confirm this expectation. Holding on- or off-peak status fixed, NYISO has the highest and PJM the lowest percent frequencies of low outliers and nonpositive prices.[14] Spot price skewness is lowest for NYISO and highest for PJM, whereas the standard deviations and IQRs exhibit the opposite pattern. Thus, greater reliance on renewables is associated with higher dispersion and lower skewness in the distribution of spot prices.

TABLE 4

Descriptive Statistics for Hourly Spot Prices in Three Markets

Table 4 provides summary statistics for hourly spot wholesale electricity prices as reported by PJM Interconnection LLC (PJM) from June 1, 2000 to Nov. 14, 2016; by the New York Independent System Operator (NYISO) from Mar. 1, 2005 to July 31, 2018; and by Independent System Operator New England (ISO-NE) from Jan. 1, 2011 to June 30, 2018. Peak hours are the 16 hours ending between 8:00 and 23:00. Off-peak hours are the remaining 8 hours of the day. Prices are dollars per megawatt hour. Low outliers are observations with values below Q1 − 1.5(IQR) and high outliers are above Q3 + 1.5(IQR), where Q1 and Q3 are the upper boundaries of the first and third quartiles, respectively, and IQR is interquartile range.

	PJM		NYISO		ISO-NE	
Variable	On Peak	Off Peak	On Peak	Off Peak	On Peak	Off Peak
Mean	47.27	28.42	52.82	35.95	47.91	34.62
Std. dev.	35.01	20.80	59.08	50.07	47.12	36.37
Skewness	11.01	9.12	4.53	−1.88	5.78	3.86
Kurtosis	354.29	246.94	170.67	158.53	82.19	37.98
Minimum	−158.98	−230.01	−2,604.16	−1,953.86	−156.60	−155.41
Q1	29.23	19.04	28.08	18.94	25.75	19.03
Median	38.12	25.31	40.18	30.40	36.20	27.15
Q3	55.43	31.81	63.09	45.16	51.04	37.79
Maximum	1,818.77	1,016.75	2,203.22	1,134.63	1,430.38	937.55
IQR	26.20	12.77	35.01	26.23	25.30	18.76
% < Q1 − 1.5(IQR)	0.02%	0.47%	0.34%	1.82%	0.15%	1.22%
% > Q3 + 1.5(IQR)	6.21%	6.85%	5.73%	7.16%	8.74%	8.04%
% ≤ 0	0.05%	1.46%	0.63%	3.38%	0.43%	2.92%
N	96,176	48,088	78,416	39,298	43,808	21,904

[14]Though not reported in Table 4, daily averages for off-peak hours are nonpositive on 2.12% and 1.68% of days for NYISO and ISO-NE, respectively. The frequency for PJM is 0.18%.

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Estimates of regression equations (3) and (4) for daily on- and off-peak average prices are reported for all three markets in Table 5. The results for NYISO and ISO-NE are largely consistent with those for PJM. First, all estimates of $\beta_{\Delta S}$ and β_P are positive and statistically different from 0 at the 0.001 level, providing evidence that the basis has predictive power for the daily changes in the spot price and for the 1-day risk premium during both on- and off-peak hours. Second, all estimates of $\beta_{\Delta S} - \beta_P$ are positive and statistically different from 0 at the 0.001 level, providing evidence that the variance of the expected change in the spot price is greater than the variance of the ex ante premium. Third, for every regression pair, the R^2 is higher for the spot price change regression, indicating that the basis explains a greater proportion of variation in the spot price change than does the premium. A notable difference in results across markets is the fact that the relative contribution of variation in the risk premium to variation in the basis is lower for NYISO and ISO-NE than for PJM. This may be because market participants have some success predicting the generally larger spot price changes in the more volatile NYISO and ISO-NE markets. Another difference for NYISO is that the slope coefficients, $\beta_{\Delta S}$ and β_P, are similar for on- and off-peak hours.

TABLE 5

Comparison of Regression Results for Three Electricity Markets

Table 5 presents regression results for PJM Interconnection LLC (PJM), New York Independent System Operator (NYISO), and Independent System Operator New England (ISO-NE). The variables for on-peak and off-peak regressions are daily averages calculated over on-peak hours (8:00 to 23:00) and off-peak hours (24:00 and 1:00 to 7:00), respectively. S_t is the spot price observed at the indicated hour on day t. $F_{t,t+1}$ is the forward price observed on day t for delivery at the indicated hour on day $t+1$. Prices are dollars per megawatt hour. D_{SUMMER}, D_{FALL}, and D_{WINTER} are dummy variables that identify the season of the year. Each off-peak/on-peak regression pair for each market is estimated as a system using seemingly unrelated regression estimation after a Cochrane–Orcutt transformation to adjust for serial correlation. Standard errors of coefficients are denoted SE (·). *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 levels, respectively.

Panel A. Regressions of Change in Spot Price and Realized Premium on the Basis

$$S_{t+1} - S_t = \alpha_{\Delta S} + \beta_{\Delta S}(F_{t,t+1} - S_t) + \varepsilon_{\Delta S,t+1}$$
$$F_{t,t+1} - S_{t+1} = \alpha_P + \beta_P(F_{t,t+1} - S_t) + \varepsilon_{P,t+1}$$

Market	Hours	$\alpha_{\Delta S}$	$\beta_{\Delta S}$	α_P	β_P	SE (α)	SE (β)	$\beta_{\Delta S} - \beta_P$	SE ($\beta_{\Delta S} - \beta_P$)	$R^2_{\Delta S}$	R^2_P
PJM	Off peak	−0.12	0.80***	0.12	0.20***	0.15	0.01	0.60***	0.03	0.30	0.02
PJM	On peak	−0.15	0.65***	0.15	0.35***	0.25	0.01	0.31***	0.03	0.14	0.11
NYISO	Off peak	−0.23	0.83***	0.23	0.17***	0.28	0.01	0.67***	0.03	0.39	0.03
NYISO	On peak	−0.50	0.82***	0.50	0.18***	0.35	0.02	0.64***	0.03	0.29	0.04
ISO-NE	Off peak	−0.02	0.93***	0.02	0.07***	0.32	0.02	0.86***	0.04	0.40	0.01
ISO-NE	On peak	−0.75	0.78***	0.75	0.22***	0.42	0.02	0.55***	0.04	0.22	0.06

Panel B. Regressions of Realized Premium on the Basis with Seasonal Interactions

$$F_{t,t+1} - S_{t+1} = \alpha_P + \beta_P(F_{t,t+1} - S_t) + \beta_S D_{\text{SUMMER}}(F_{t,t+1} - S_t) + \beta_F D_{\text{FALL}}(F_{t,t+1} - S_t) + \beta_W D_{\text{WINTER}}(F_{t,t+1} - S_t) + \varepsilon_{P,t+1}$$

Market	Hours	α_P	β_P	β_S	β_F	β_W	SE (α_P)	SE (β_P)	SE (β_S)	SE (β_F)	SE (β_W)	R^2_P
PJM	Off peak	0.11	0.25***	0.17**	0.06	−0.09	0.15	0.04	0.07	0.07	0.05	0.02
PJM	On peak	0.12	0.20***	0.13**	0.04	0.19***	0.25	0.04	0.05	0.06	0.04	0.12
NYISO	Off peak	0.22	0.11***	0.07*	0.06	0.07*	0.27	0.03	0.05	0.05	0.04	0.03
NYISO	On peak	0.50	0.09**	0.05	0.01	0.20***	0.33	0.04	0.05	0.06	0.04	0.05
ISO-NE	Off peak	0.02	0.01	0.18**	0.16*	0.05	0.31	0.05	0.09	0.09	0.06	0.01
ISO-NE	On peak	0.70	0.13**	0.07	0.00	0.16**	0.41	0.06	0.08	0.09	0.07	0.06

Panel B of Table 5 presents results of estimating the relation between the risk premium and the basis with seasonal effects. The evidence confirms seasonal effects for all three markets. Whereas the summer seasonal is significant for PJM both on peak and off peak, it is significant only off peak for NYISO and ISO-NE. For each market, the winter seasonal is significant for on-peak hours only.

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Figure 4 shows graphs of recursive slope coefficient estimates and 95% confidence intervals for the risk premium regression (4) for daily off-peak and daily on-peak average hourly prices for NYISO and ISO-NE. The graphs exhibit some similarities and some differences from those for PJM. The off-peak slope coefficient for NYISO is very stable with only a slight perturbation in Jan. 2014, the month of the polar vortex event, whereas the on-peak hour slope coefficient for NYISO increases in Jan. 2014, similar to the coefficient for PJM. An unusual aspect of the recursive results for ISO-NE is a marked increase in the slope coefficient for both on- and off-peak hours during 2013. Two occurrences may explain this increase. Wholesale electricity prices in New England rose 55% that year because of high and increasing demand for natural gas combined with pipeline (supply) constraints. In the same year, ISO-NE announced its intention to replace coal- and oil-fired and nuclear power plants representing 16% of the region's generating capacity with wind and natural gas sources between 2013 and 2021. The off-peak hour slope coefficient for ISO-NE decreases markedly in Jan. 2014, similar to the coefficient for PJM. The on-peak slope also decreases in Jan. 2014, contrary to the increases for PJM and NYISO. Important enhancements to the New England Energy Market implemented in 2014 likely played a role in the decline in the variances of both on- and off-peak risk premiums after 2013. These changes included the ability to change price and supply offers hourly to reflect changing fuel costs, and the opportunity to submit negative price offers.[15]

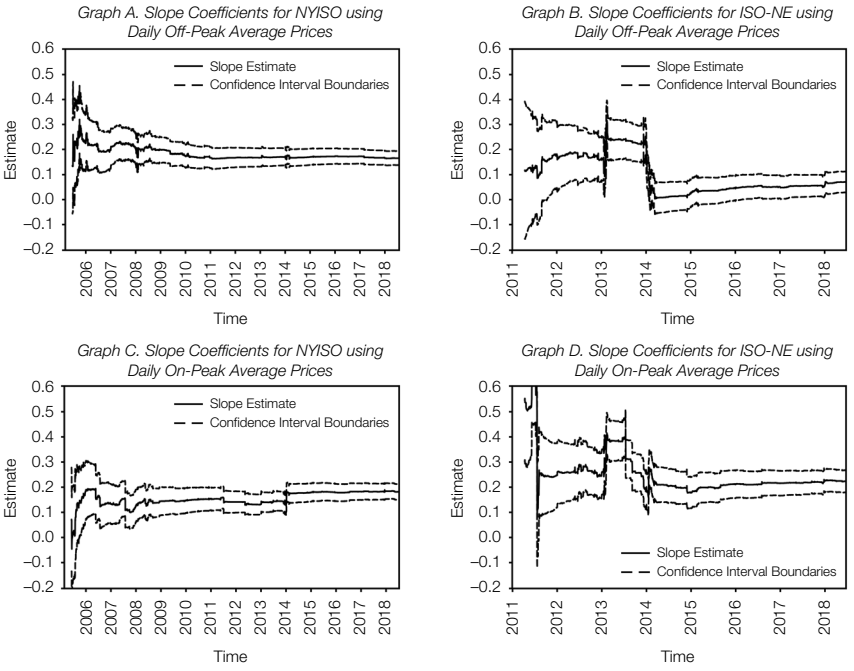
VI. Conclusion

We present evidence that day-ahead forward prices for electricity on PJM contain time-varying spot price forecasts and ex ante risk premiums that enable the basis to predict realized spot price changes and risk premiums each hour of the day and season of the year throughout the life of the day-ahead market. Our evidence that the basis has forecast power for spot prices and risk premiums in electricity markets stands in contrast to the much weaker evidence reported for other commodities. We attribute our stronger results to two aspects of electricity. First, electricity is not cost effectively stored, so inventory is not available to smooth the effects of variable demand and supply on spot prices. Second, seasonal and hourly variation in the level and volatility of demand and supply produce seasonal and hourly variation in expected spot prices, the likelihood of price spikes, and the likelihoods of low and negative prices. Price shocks are often extreme because of an absence of storage. These aspects of electricity markets combine to produce substantial temporal variation in spot prices and the needs for producers and retailers to hedge against extreme spot price decreases and increases, respectively. Time-varying hedging needs imply time-varying risk premiums. Evidence that time-varying risk premiums persist in the mature PJM market supports the conclusion that risk premiums represent rewards for economic risk rather than a lack of market learning or efficiency. Positive and statistically significant median risk premiums indicate that more often than not, sellers of day-ahead forward

[15]For a timeline of key events in the history of ISO-NE, see https://www.iso-ne.com/about/what-we-do/history.

FIGURE 4
Recursive Risk Premium Regressions for NYISO and ISO-NE

Figure 4 illustrates the results of recursive estimation of risk premium regressions for the independent system operator (ISO) markets of New England (ISO-NE) and New York (NYISO) over the periods Mar. 1, 2005 to July 31, 2018 and Jan. 1, 2011 to June 30, 2018, respectively. Graphs A and B (Graphs C and D) display recursive slope coefficients and 95% confidence intervals for the daily average of off-peak (on-peak) hour premiums for NYISO and for ISO-NE. We require a 100-day minimum to estimate the system.



contracts earn a positive premium at the expense of buyers, rather than vice versa (often assumed to be the case for commodity markets).

Our evidence that the basis has power to predict spot price changes and risk premiums in three power markets suggests that using the basis as a predictive variable has the potential to relate predictability, risk, and return across electricity markets and over time. The predictive success of the basis across electricity markets is likely due to its ability to reflect market participants' expectations conditional on a variety of market-specific information.

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