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Does Generation Investment Follow Locational Price Signals? Long-term Evidence from the PJM Electricity Market

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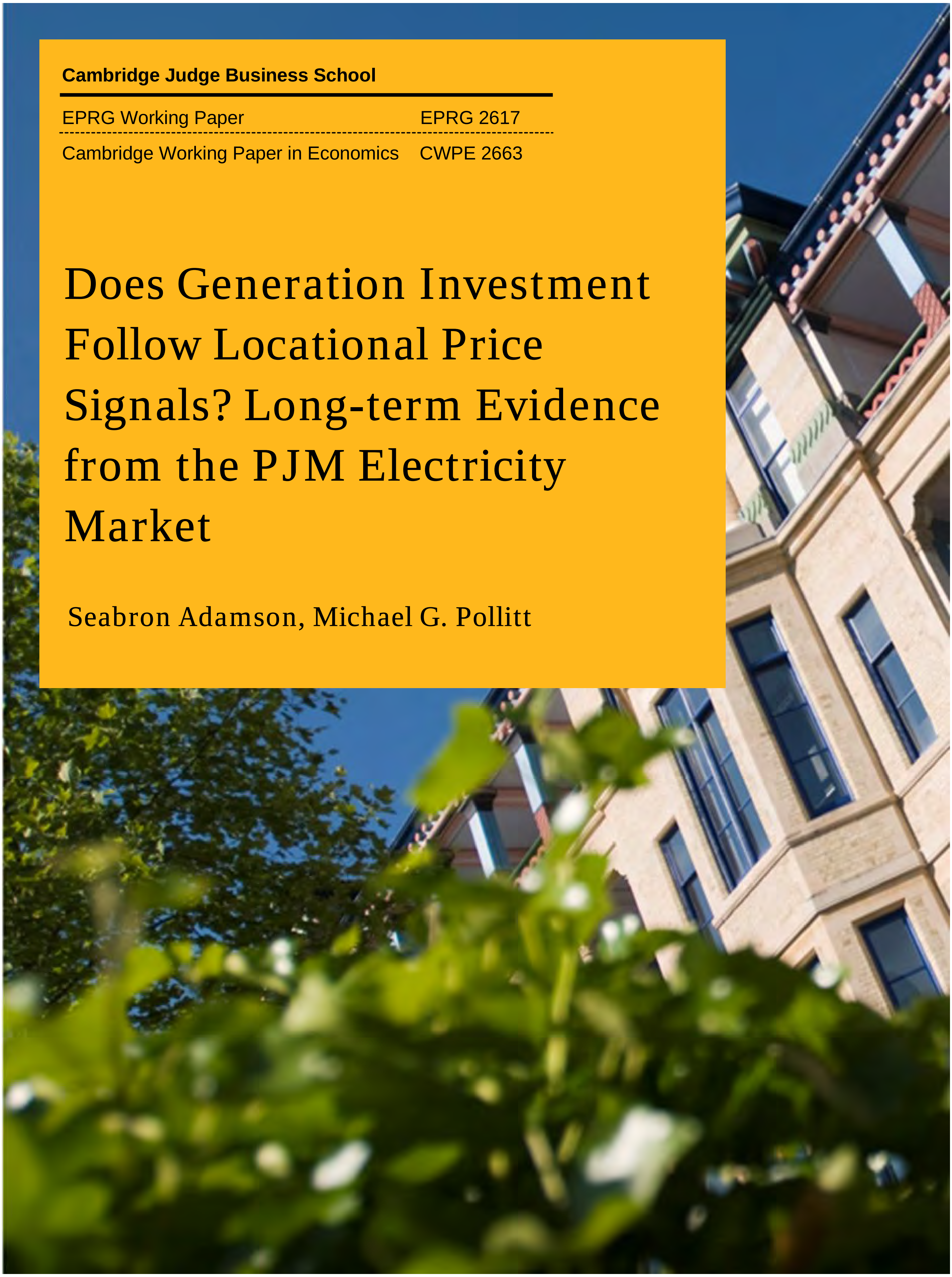

Energy Policy Research Group

UNIVERSITY OF CAMBRIDGE
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Keywords : locational marginal pricing (LMP), investment, PJM, trading hubs, logistical regression.

JEL Classification : L94, Q42, Q48

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30 June 2026

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A major claim for the benefits of locational marginal pricing (LMP) in electricity markets has related to increased efficiency in locational investment decisions. However, there has to date been little empirical evidence for this claim. Using a very large dataset of more than 1000 new plant investments in PJM over more than 20 years, we test whether LMPs have shaped investment decisions using quartiles and logistical regression techniques. We show that LMPs and locational capacity prices have been statistically significant in relation to where investments in solar and gas-fired generation across PJM, but not for wind generation. We also show that on an intrazonal basis LMP differences appear significant with respect to locational investment decisions for new solar generation within the Dominion zone of PJM. Finally, we note that while LMPs over longer periods of time are difficult to predict as they reflect natural gas prices and other economic variables, LMP basis differentials to a small number of traded hubs are much more predictable, consistent with new generators being able to hedge most price risks at a small number of traded hub prices.

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1. Introduction

A continuing debate in electricity market design is the value in locational granularity of power prices. Hourly or sub-hourly prices in power markets serve multiple functions, such as signals for unit commitment and dispatch, settlement of forward trading and hedging contracts, and as investment signals for new generation and consumption. More efficient generation investment decisions arising from improved pricing signals are frequently cited as an advantage of locational marginal pricing (LMP) systems over zonal or single price electricity markets. A key focus of the current paper is examining how much these LMP and other locational price signals affect generating investment decisions in practice.

Organized markets in the United States have over time shifted to LMP-based systems based on security-constrained economic dispatch (SCED) mechanisms (Hogan, 2019). In these markets, competition is bid-based, and an independent system operator (ISO) uses an optimized SCED system to generate economic dispatch signals and locational prices. The origins of this fundamental structure, in which prices at locations on the grid reflect transmission constraints, date to the 1980s and the spot pricing work of Schweppe *et.al.* (see for example Schweppe, Caramanis, Tabors and Bohn, 1988 and Bohn, Caramanis and Schweppe, 1984). The PJM electricity market began real-time LMP pricing in 1997. The PJM day-ahead LMP market started in June 2000.

Other countries have also adopted the LMP framework. New Zealand was the first region to adopt LMP in its concurrent restructuring of its hydro-dominated power system in 1996 (McRae, 2025). The IESO market in Ontario, Canada commenced operations in May 2025 (IESO, 2025). In August 2025 it was announced that the Alberta electricity market, one of the earlier competitive wholesale power markets, would convert to LMP in 2027 (AESO, 2025).

Europe has so far resisted adopting the LMP framework, focusing instead on the creation of a single European electricity market using algorithmic coupling of national and regional power markets. Most markets within the European Union currently operate as bidding zones based on national borders. These national border-based bidding zones do not reflect actual transmission constraints in EU grids, and European transmission system operators (TSOs) have recently undertaken a review of bidding zones which could involve splitting national zones into smaller zones (ENTSO-E, 2025).

Various countries in Europe have considered LMP instead of larger pricing zones. Poland considered an LMP electricity market but this was not implemented (PSE, 2018). More recently, the United Kingdom considered a LMP design in its recent review of electricity market arrangements. Proponents of this option argued that adoption of LMP in the GB market would create substantial benefits, significantly because of better locational pricing signals (FTI Consulting, 2023). In the end, the British government chose to keep a single pricing zone for the GB market (England, Wales and Scotland) and focus on other reforms (DESNZ, 2025).

The paper is organized as follows. Section 2 reviews the literature on locational prices and generation investment. Section 3 discusses the operation of the PJM market. Section 4 looks at the theory of investment decision making in an LMP market. Section 5 presents the data and reviews the descriptive statistics. Section 6 reports the econometric analysis of generation siting decisions. Section 7 examines the investment impacts of intrazonal LMP differentials. Section 8 contains an analysis of LMP basis differentials within hub regions. Section 9 concludes and discusses implications for power market design and further research.

2. Locational prices and generation investment

A significant claim for the benefits of locational pricing over less granular methods such as national zones is improved efficiency in system operations and in the siting of generation investment. Short-run operational efficiencies are not the focus of this paper, but can be important (Wolak, 2011). Most empirical studies of LMP efficiency gains have focused on forward-looking, simulation model-based assessments of system operations and evolution, which seek to quantify short-term operational gains from more efficient use of the transmission system and improved optimization of unit commitment, dispatch and ancillary services procurement. Various studies of the U.S. independent system operators generally fall into his category, including studies of the ERCOT market in Texas (CRA, 2008). Richard Green has analyzed the GB system in a simplified nodal model and found that a fully nodal design would have had a small improvement in dispatch efficiency and would be less susceptible to exercising market power (Green, 2007). Other analyses of grid versus zonal designs based on modelling of simplified systems include the European-focused analyses of van de Wijde and Hobbs (van de Wijde and Hobbs, 2011) and Oggioni and Smeers (Oggioni and Smeers, 2012).

A second strand of simulation model-based analyses has included generation investment decisions in modeling nodal, zonal and single price market designs. In the UK government's recent review of LMP, FTI estimated that a fully nodal LMP solution would provide approximately twice the benefits of a zonal solution (FTI Consulting, 2023). Improvements in long-term electricity generation siting decisions were a part of the total modelled gain from nodal pricing. The absolute size and relative significance of the net benefits were questioned by other analysts (Frontier Economics, 2022; Pollitt, 2023). The theoretical arguments for more efficient locational generation siting of intermittent resources have been well explored (see for example Newbery and Biggar, 2023).

Despite the importance of long-term investment decisions in the policy debate, there has been surprisingly little direct empirical analysis of LMP market outcomes. Most studies focus on short-run dispatch decisions (e.g., Trioli and Wolak, 2022) and there is little published evidence on whether generation investors in practice rely on LMP pricing signals in choosing where to invest. For instance, Triolo and Wolak examined the short-term generation operations in the ERCOT market in Texas before and after the implementation of LMP. Their analysis found that generator operating costs fell for the same level of output after the implementation of LMP, although heat inputs and carbon emissions rose slightly.

The only major study of generation siting under LMP of which we are aware is the ERCOT analysis of Brown *et. al.* (Brown, Zarnikau and Woo, 2020). Their analysis focuses on the energy-only ERCOT market in Texas over an eight-year period from 2011 to 2019. Using descriptive statistics and regression modeling the authors find limited evidence that higher recent LMPs drive generation investment decisions, and they report that the statistical significance of many of their regression results are rather weak and dependent on model specification.

In this paper, we test whether investors in new generation have been guided by locational prices, using a large dataset of generation investments in the PJM electricity market since 2000.

We rely on analysis of the PJM market for multiple reasons. The PJM market is by far the largest LMP market in terms of capacity, covers a wide range of geographies and states (unlike ERCOT for example, which operates solely within Texas), and has been operating as a restructured LMP market for over 25 years. This allows for a longer time horizon of analysis, important when examining investment in large, lumpy generating plants. The PJM market has been viewed, within and outside the United States, as the premier example of LMP market implementation (see, for example, Glachant *et al.*, 2021).

Analysis of PJM provides other key advantages for study of electricity market design. Like many U.S. LMP markets, PJM has a separate capacity market with locational capacity prices. The forward-looking mechanism used in PJM is broadly like those in many other capacity markets such as the UK, which operates auctions allowing capacity suppliers to secure capacity agreements up to four years in advance (NESO, 2025) For renewable assets, especially solar, the PJM states have different solar renewable energy credit (SREC) mechanisms which provide state-level incentives as well. Analyzing PJM locational investment choices allows the impact of different locational pricing mechanisms (hourly LMPs versus annual capacity prices and tradable RECs) to be examined explicitly.

Our analysis also includes additional important methodological developments over previous studies. Given the long and large data set available, we analyze the entry decisions of over 1000 individual plants over a period of over 20 years. Our analysis uses LMPs but also locational generator margins (often referred to as "spark spreads") for gas-fired plants, since LMPs vary with locational daily natural gas prices. Due to the geographic extent of the PJM market, we also analyze the impact of locational gas prices at different gas hubs, which was not included in previous analyses. Given the high degree of correlation between LMPs across the market region, as discussed below, we pay special attention to multicollinearity across pricing nodes in the panel data. Finally, we note that since LMPs over the longer terms relevant for generation investment are difficult to predict, we analyze how stable local

LMPs are in relation to trading hub prices over long periods to determine if generation investors should be able to form reasonable expectations of LMP basis differentials (e.g., between a generator node and a recognized price hub) in order to contract, consistent with the expectation that most generation investment is backed by offtake contracts or hedges to help mitigate price risks.

3. The PJM electricity market

The PJM market serves over 57 million people and covers all or part of 13 states and the District of Columbia, extending from northeastern North Carolina to New Jersey and west to Chicago. PJM is one of the world's largest electricity markets and historically has been the largest LMP-based market with a peak load of over 161 gigawatts (GW) and installed capacity of approximately 200 GW. The PJM service territory has seen rapid generating capacity growth in recent years, especially of new renewable generation. PJM has also grown over time as neighboring regions have joined.

Given our focus on the responsiveness of generation investment to local price signals, we focus here on the prices that will affect PJM generator revenues These include energy prices, as reflected in LMPs, capacity prices under the PJM Reliability Pricing Model (RPM) capacity market construct, and renewable energy credit (REC) prices which may vary by state within PJM.

3.1. PJM Energy Markets

Temporally, PJM operates day-ahead and (DA) and real-time (RT) LMP markets for energy. The DA market is integrated with the security-constrained unit commitment process for generator and load scheduling and produces an hourly LMP for the next day. The DA LMP energy market in PJM is also co-optimized with the ancillary services markets. Most volumes in PJM are traded in the DA market, exceeding 90%.

In real-time, PJM performs economic dispatch and generates real-time LMPs. Any long or short positions from the DA market are cleared at the RT spot price. Unlike the hourly DA market, RT LMPs are set every five minutes.

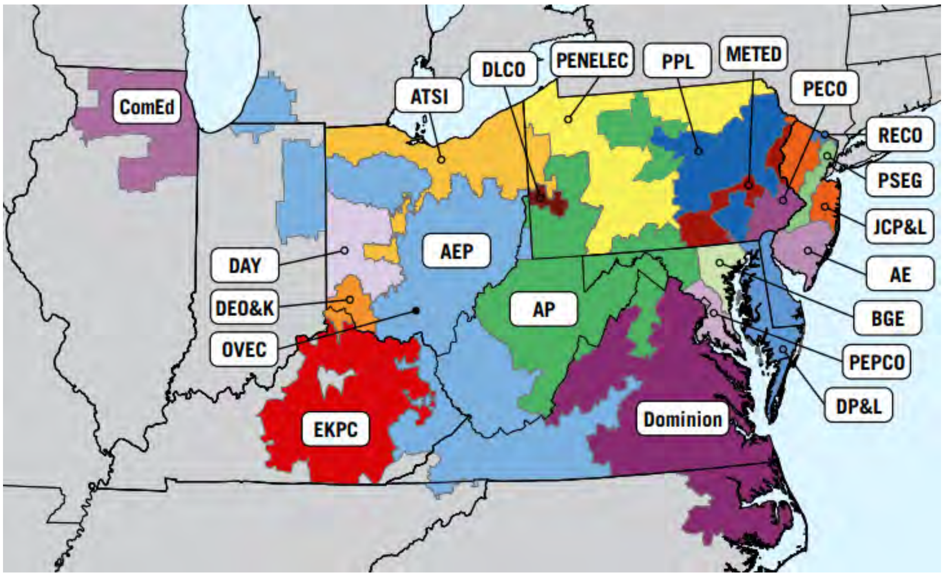
Spatially, PJM currently calculates and publishes LMPs at over 11,000 nodes (GridStatus, 2025). Pricing at these nodes reflect contemporaneous expected and actual transmission constraints during unit commitment (DA) and dispatch (RT). PJM also publishes hub prices (which reflect the LMP at some number of pricing nodes for trading purposes) and zonal prices, which reflect load-weighted average nodal LMPs over a defined region.

Larger generators (over 1 MW, as analyzed in this paper) are paid the prevailing LMP at their pricing node (pnode) for their output.[1] While some large loads pay a nodal price, most loads are served by local distributors and pay a zonal price.[2] The zonal boundaries in PJM largely follow the ownership of the transmission utilities, as shown in Figure 1 below.

Figure 1 PJM Load Zones

[1] There have been numerous small generators (< 1.0 MW) added, especially solar photovoltaic plants in recent years. However, many of these are tied to commercial or industrial loads and hence are less likely to have siting decisions driven by wholesale electricity market pricing.

[2] Load serving entities (LSEs) with appropriate metering infrastructure and meeting other requirements can elect to pay nodal rather than zonal prices, as described in PJM Manual 27 (PJM, 2025).



Source: PJM. Used by permission of PJM.

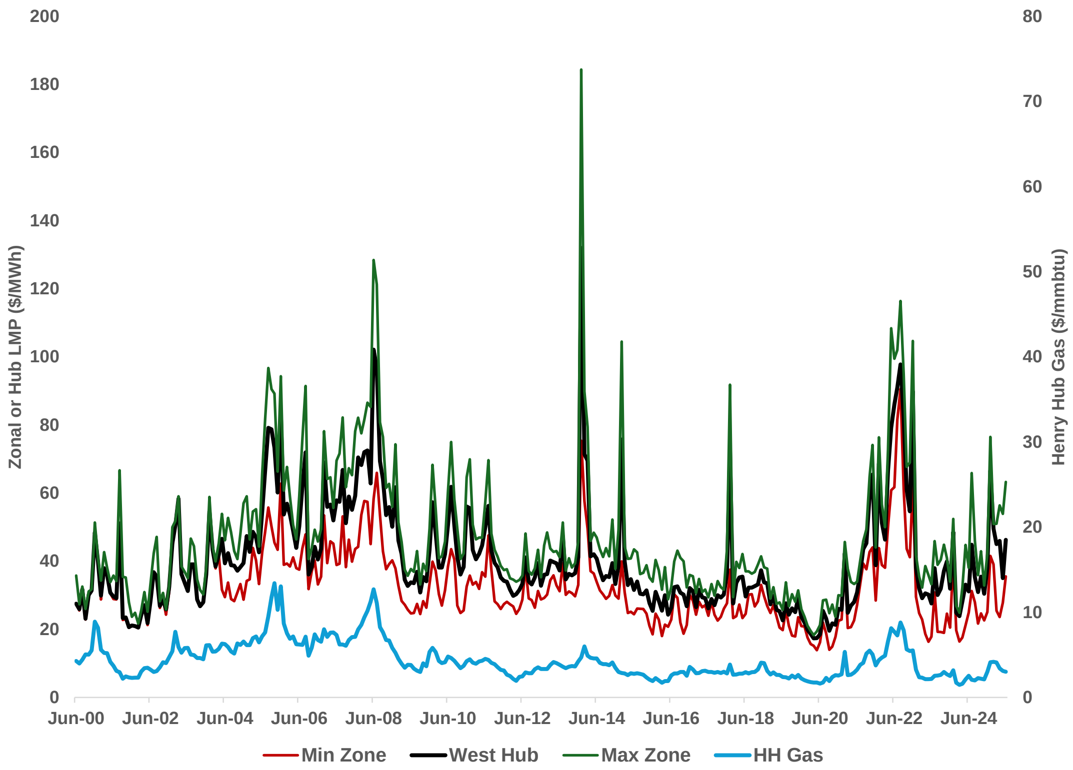
Conceptually, the LMP at each node represents the short-run marginal cost of providing an additional unit of electricity at each node *I* at each time *t*. This is represented by three elements: the system marginal energy cost (SMEC), the marginal congestion cost (MCC) and marginal loss cost (MLC) as shown in the equation below:

$$LMP_{i,t} = SMEC_t + MCC_{i,t} + MLC_{i,t} \qquad (1)$$

The SMEC represents the marginal cost of adding an additional unit of energy to the system as a whole and hence is not dependent on location on the grid. However, due to the presence of transmission capacity constraints on the grid, generation must be re-dispatched so that the resulting flows do not exceed maximum flows across the grid, which creates marginal congestion costs (MCC) which vary by each location. Marginal congestion costs may be positive or negative, depending on the impact of additional load at any node on total system congestion costs. Similarly, the MLC term represents the contribution of load at node *I* to total system losses. These may also be positive or negative.

Since LMPs across the market share the same SMEC, LMPs across the market tend to be highly correlated. Figure 2 shows the evolution of monthly average DA LMPs over the 25 years since the DA market was launched in June 2000, showing Western Hub (a trading hub where many forward contracts are settled) and the average monthly LMP in the highest and lowest priced zones in that month. The chart also shows monthly Henry Hub gas prices for the corresponding months.

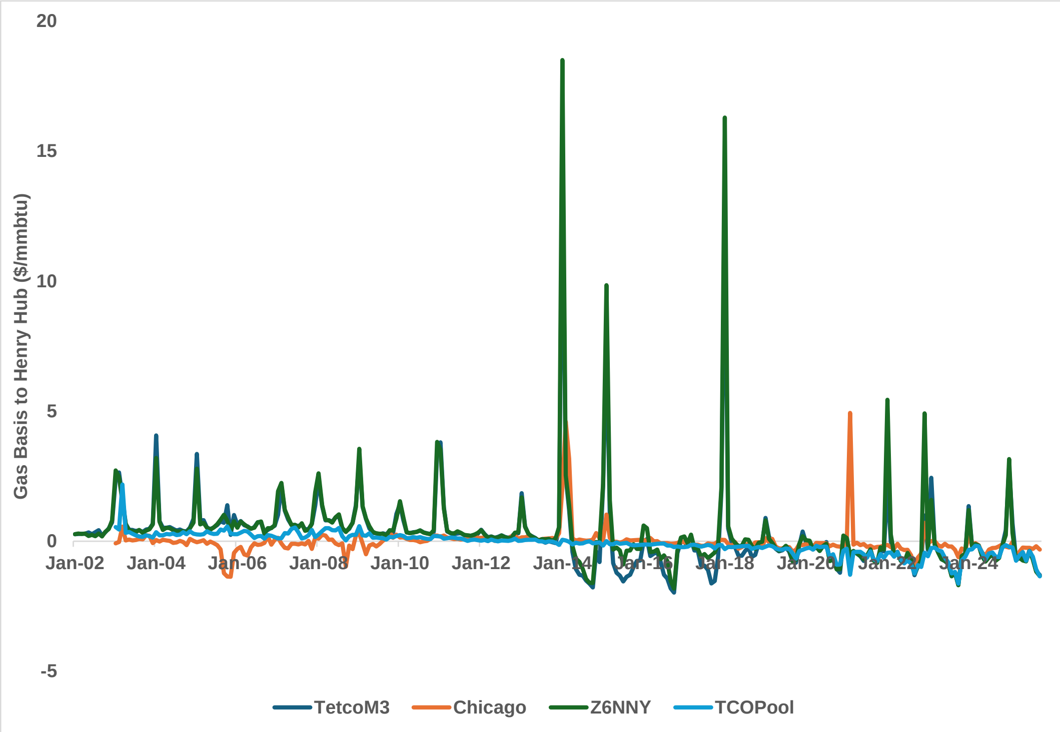
Figure 2 Monthly DA LMPs (Mix/Max Zonal and Western Hub) and Henry Hub gas prices (right-hand scale)



LMPs are significantly affected by natural gas prices. However, the PJM region is large and different regional gas hub prices apply in different locations within the market. Local gas prices differ due to pipeline transportation costs and congestion in the gas transmission system. Since generators use gas at various locations within the PJM region, these local gas prices (which can differ substantially from Henry Hub prices in some periods, especially in winter) also affect generation costs and PJM LMPs. Figure 3 shows monthly gas price basis at four major trading points within the region.[3]

Figure 3: Gas price basis (monthly) within the PJM region

[3] Z6NNY refers to Transco Zone 6 (non-New York), reflecting gas transactions in the northeast section of PJM such as New Jersey and surrounding areas. Tetco M3 refers to trades on the Texas Eastern pipeline (pricing zone M-3) which reflects basis to Pennsylvania and surrounding regions, and TCO Columbia Pool covers a major gas producing area served by the Columbia Gas Pipeline system. Chicago in this case refers to Chicago Citygate prices. Gas basis shown in local hub gas prices relative to Henry Hub.



Like LMPs, gas prices are highly correlated, and in many months basis differentials to Henry Hub are modest. However, there are occasional winter spikes due to pipeline constraints especially in Zone 6 NNY. These winter basis spikes, reflecting high purchase gas costs in eastern PJM, may also impact LMPs in eastern PJM. The negative price basis seen in some recent years for TCO Pool and Z6NNY in summer months reflect high levels of production in the Marcellus shale region and pipeline constraints in moving gas out of the producing region.[4]

3.2. PJM Capacity Market

The current Reliability Pricing Model (RPM) in PJM started in 2007. Prior to 2007, the capacity market in PJM, like that in other U.S. markets, was for short-term capacity products acquired shortly before the delivery period. The RPM design gradually shifted to a forward capacity construct, in which capacity is procured now for delivery in three years. Procuring capacity forward makes the market more contestable as new plans have more time to enter the market over this three-year period. The amount of capacity needed in each capacity load zone is set by PJM, based on forecasts of load growth.

The value of capacity resources depends on availability to generate during periods of extreme weather conditions or large outage events. PJM has historically used availability factors to determine the extent to which different classes of capacity resources can be relied upon to supply energy in critical periods. Performance tests for generating units selling capacity are also used to ensure capacity amounts (which may vary by season) can be met. In 2024, the Federal Energy Regulatory Commission (FERC) approved new rules determining capacity quantities based on effective load carrying capacity (ELCC). The ELCC methodology rewards generating resources on a marginal basis that are expected to be operable in high-risk hours (e.g., capacity that can run in periods of high demand and otherwise lower capacity output).

While needed capacity in each PJM load zone is set individually, the capacity auction clearing mechanism used is more complex to account for the ability of capacity in one zone to help meet capacity needs in other zones. For purposes of the PJM capacity market loads and capacity

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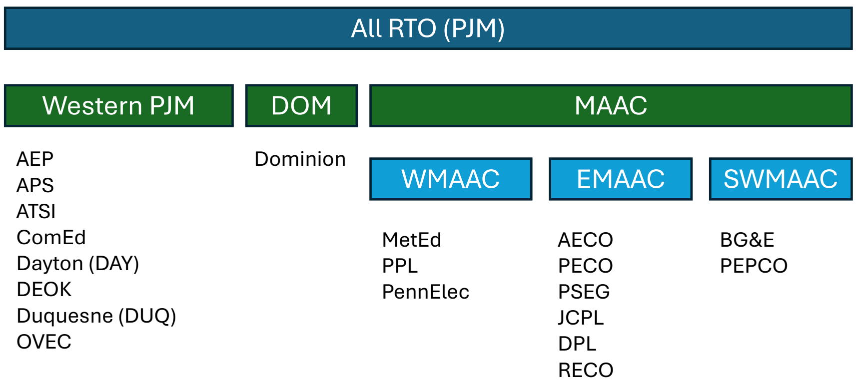
4 Gas is traded in daily markets and prices in basis on a daily basis, especially in winter, is generally even more volatile.

resources are grouped into 27 Local Deliverability Areas (LDAs) which generally reflect the zones shown in Figure 1 above.[5] However, the capacity auction structure nests these 27 individual LDAs into larger parent zones, and capacity prices in PJM generally clear at this larger zonal level.

The nested structure of the 27 LDAs and larger parent LDAs is illustrated in Figure 4 below.[6] The structure of the auction ensures that the capacity price within an LDA clears at or higher than the parent LDA above, so for example, p(PPL) >= p(WMAAC) >= p(MAAC) >= p(RTO). In a few cases individual LDA capacity prices have cleared above the regional/sub-regional price, but this is relatively infrequent.

Figure 4 Nested PJM Load Delivery Areas



Prices under the RPM capacity market have been quite volatile, as shown in Figure 5. Prices are shown for the delivery year, which starts on June 1 and ends on May 31 the following year.[7] Not shown (but reflected in our analysis) are prices in individual LDAs (such as BGE, ATSI, PSEG and DOM) which have occasionally cleared higher in a few years. Prices are denominated in dollars per megawatt of capacity per day. The capacity that any generating unit can sell is adjusted by the availability/ELCC factor, so a combustion turbine unit, for example, would likely get a much higher capacity value per megawatt of installed capacity than a wind farm.

Figure 5 Capacity prices in major PJM regions and sub-regions

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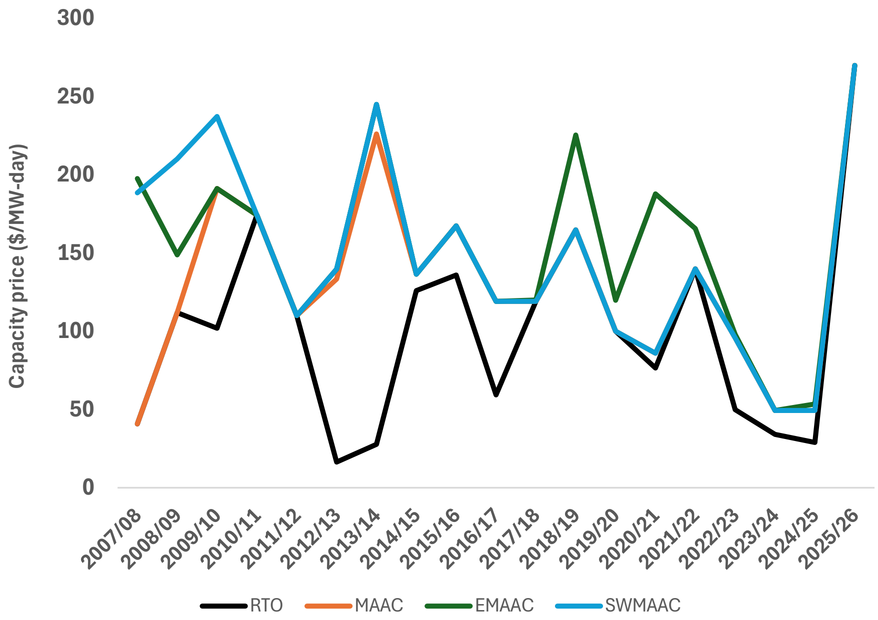
5 For capacity modelling purposes, a few capacity zones such as DPL and PSEG have smaller defined sub-zones. These however very rarely clear separately from the broader load zone.

6 The parent LDA names reflect historical NERC reliability planning zones within PJM. MAAC reflects for the Mid-Atlantic region, and WMAAC, EMAAC and SWMAAC sub-regions reflect western, eastern and southwestern regions within MAAC. All RTO (for "Regional Transmission Organization") reflects the base value of capacity across the PJM region. For more details on the RPM design see the PJM Capacity Manual (PJM, 2025).

7 The 2021/22 Delivery Year, for example, started on June 1, 2021 and ended on May 31, 2022. WMAAC prices have not cleared differently from broader MAAC prices historically and hence are not separately reflected in the figure.



In broad terms, capacity prices as reflected in the RPM base residual auctions are higher in eastern PJM (the EMAAC and SWMAAC zones), where loads and new construction costs are higher. Capacity prices rose sharply for delivery in the 2025/26 Delivery Year across the entire PJM footprint.

Starting with the 2016/17 Delivery Year, some capacity resources in PJM are subject to capacity performance standards, in which units selling capacity and which are not available in a Performance Assessment Interval (PAI) are subject to penalties. Conversely, units which outperform their capacity delivery obligation are eligible for bonus payments. As of the 2020/21 base residual auction, all PJM capacity units were subject to this penalty/bonus scheme (PJM, 2018).

3.3. State Renewable Incentive Mechanisms

While not directly part of the PJM market structure, many of the states within the PJM market area have renewable energy support programs. These programs typically require load serving entities (LSEs) such as retailers and utilities which serve load to purchase a defined fraction of their energy sales from qualifying renewable energy production. In many states, regulations require certain percentages of total renewable energy to be sourced from specific resources such as solar. LSEs can either procure power under contract to source renewable energy or purchase tradable renewable energy credits (RECs) to meet their obligations, which are typically defined over a year. Some states allow RECs to be sourced (for some types of renewables) from other states, creating a broader market for some types of RECs.[8]

In PJM, the most important renewable incentive programs have supported solar PV, and which are reflected in solar REC (SREC) pricing which varies over time and by state. This mechanism has provided strong incentives in some years to build solar PV capacity in locations such as New Jersey where it would otherwise be uneconomic.

Figure 6 SREC prices (annual weighted average) across the PJM states

[8] For a discussion of state renewable energy incentive programs and REC market dynamics see Raikar and Adamson, 2024.

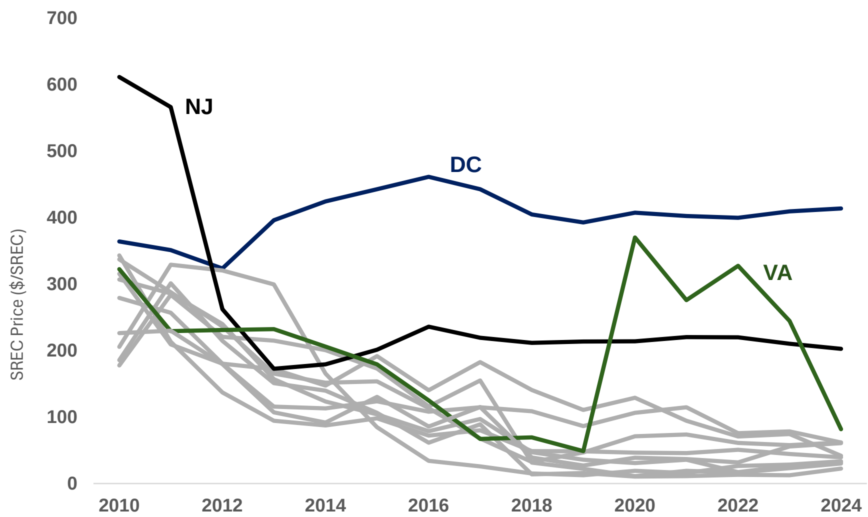


Figure 6 above shows the evolution of SREC prices over time across eleven PJM states and the District of Columbia (DC). Prices depend on state level supply-demand balances in many cases and can be very volatile; the figure shows weighted average SREC prices for all compliance SRECs created or traded in the year by state where the solar generation is located. DC SREC prices are very high but apply only to a small amount of solar generation, given the small geographic area of DC which is only the city of Washington. New Jersey (NJ) had aggressive solar targets and high SREC prices. Virginia (VA) has seen substantial solar PV investment. Other state SREC prices (shown in grey) have generally been correlated and have declined sharply as the cost of new PV generation has dropped.

Wind generation is also supported by REC mechanisms, but the prices are substantially lower and less differentiated by location. Wind and solar projects are also subsidized through federal tax credit mechanisms such as the Production Tax Credit (PTC) and Investment Tax Credit (ITC). These credits do not vary by location and hence provide no direct locational signals for investment (Raikar and Adamson, 2024).[9]

4. Locational market signals and investment decisions

We consider a two-part investment model for generation investments, where capital costs are significantly sunk. At time *t*=0, an investor must decide whether to invest in a generation technology *j* at a specific node *i* on the grid. In general, the revenues and costs of an investment will vary by time, location and technology choice. There is in general a substantial lag time *k* (measured in years) between when the final investment decision is made for a technology at a location and when the new generator starts producing power and revenues.

In simplified terms (and ignoring salvage value of generation assets), the expected profitability π of a generation investment given a discount rate *r* may be represented as:

$$E\left[\pi_{i,j,t}\right] = -E\left[C_{i,j,t}\right] + E\left[\sum_{t=t+k}^{t=t+k+el} \frac{\left(R_{i,j,t} - F_{i,j,t} - FOM_{i,j,t} - VOM_{i,j,t}\right)}{(1+r)^t}\right] \quad (2)$$

9 Most windfarms have historically received the PTC, which is paid at a fixed rate per unit of generation and does not vary by time, season or location. The PTC creates incentives to build windfarms in areas with higher capacity factors rather than where LMPs are highest. The ITC is based on investment costs and is unrelated to output.

The overnight capital cost C per megawatt of new capacity varies significantly by technology and may change over time. Even for a given technology, capital costs may vary by location, due to variation in interconnection costs, site differences and land costs, labor costs and other variables. The cost expectations of individual generators with respect to technology and location are private and unobservable.

Once the plant starts operations at time $t+k$, an unhedged plant will earn future revenues $R_{i,j,t}$ through its economic life el related to market prices and quantities (generation in MWh and capacity in MW) that vary by output, availability and market prices. Net revenues for thermal plants will be reduced by fuel costs $F_{i,j,t}$ and variable operational maintenance costs $VOM_{j,t}$. All plants will have fixed operations and maintenance costs $FOM_{i,j,t}$ which vary over time and technology.[10] In this simple investment model future net revenues are discounted at a single discount rate r which is independent of technology choice and time invariant.

As with capital costs, the future expectations of market revenues and operating costs of individual generators are private. Market revenues $R_{i,j,t}$ will vary significantly by hour and season, and over the life of a generation investment will depend on changes in power demand, input prices (such as natural gas costs, but also the costs of competing new generation), government policies and a wide range of factors. Since capital and operating cost expectations of investors are private, the focus in our analysis will be on locational variation in revenues, which are a function of locational energy (LMP) and capacity prices.

As was seen in the monthly price data in Figure 2, the variability in LMPs over time is very large. Capacity prices have also proved quite volatile. Absent some form of offtake contract (which could be a power purchase agreement or some form of financial hedge), generation equity investors and lenders would be exposed to high expected variability in returns over the life of a generation asset. For this reason, most new generation investments are at least partially hedged.

Hedging energy price risk in LMP markets must account for the locational basis between where a generator is located at node I and the hedge price node n. There are various possible cases here. For example, historically many new generation projects had long-term power purchase agreements (PPAs) with utility offtakers where power would be purchased at the generator location ("at the busbar"). In this case, the offtaker absorbs any LMP basis risk.

Another common structure has energy sales made at a hub LMP price h agreed by the parties. In this case, the generator faces the hourly LMP price differentials between its pricing node i and the hub LMP h. The offtaker absorbs the basis risk from the hub to the node where power is consumed.

For a hedged generator, the revenue term $R_{i,j,t}$ can be decomposed into hedged and unhedged energy and capacity components. Assume that a fraction P of the generator's output (covering the same fraction in energy and capacity terms) is sold at a hedge price LMP_{he} for energy and p_{hc} for capacity.[11] The revenue in each period can be expressed as:

$$R_{i,j,t} = P_t\left(LMP_{i,t} * q_{i,j,t} + CapPrice * Q_{i,j,t}\right) + (1 - P_t)(LMP_{he} * q_{i,j,t} + CapPrice * p_{hc}) \quad (3)$$

10 Solar and wind generators typically have minimal variable operations and maintenance costs and so all of these operating costs are generally treated as fixed for these technologies. In theory operations and maintenance costs could vary by location but this variation would normally be minimal.

11 We assume here that any capacity hedge is struck at the same zonal price as where the generator is located. Some hedges cover LMPs while others may cover energy, capacity and other products.

Such a hedge structure lowers the variability in generator revenues and returns but exposes the generator to a basis risk proportional to $B=\Sigma\,[P_t(LMP_{i,t} - LMP_{h,t})]$. If generators hedge a significant amount of their energy risk exposure at hubs, a significant question is whether generators can form reasonable expectations of their basis risk *B* to make such hedging strategies practical.

Generators also face quantity risks in hedging, especially for renewable generators such as wind farms where output is inherently uncertain. For hedged firm volumes, any quantities not supplied must be covered at out-turn LMPs, so a windfarm for example which had contracted to supply 100 MWh in every hour of a month but only supplied 90 MWh on average would face the LMP price risk on the quantity not supplied. For this reason, renewable generators will often contract at a lower level of average output with a high probability that actual generation will exceed this amount.[12]

In a later section we test the predictability of hub to node basis is a simple OLS framework. At this stage, we note that on an annual basis at least that hub and node prices tend to be highly correlated, suggesting that hub prices can be used to hedge long-term LMP risks.

Table 1 below shows the annual correlation between zonal LMPs in each year and corresponding LMPs at three PJM trading hubs.[13] The high degree of correlation between hub and nodal prices reflects lower basis risks, as the basis risk is in general proportional to the covariance of hub and nodal prices.

12 Some renewable off-take contracts, especially traditional power purchase agreements (PPAs), are unit contingent, implying that the generator is only hedged for the volumes generated. For a more complete description of renewable hedging mechanisms in LMP markets see Raikar and Adamson (2024).

13 These are the Western Hub, Eastern Hub and Northern Illinois Hub. PJM also publishes additional hub prices. The table shows the correlation of the relevant PJM zone to the trading hub with the best correlation.

Table 1 Correlation of zonal LMPs and trading hubs

Zone	AEC	BGE	DPL	JCPL	MET	PEC	PEN	PEP	PPL	PSEG	APS	AEP	COM	DOM	ATSI	EKPC	OVE
2000	0.96	1.00	1.00	0.96	0.99	0.97	0.98	0.99	0.99	0.95							
2001	0.99	1.00	1.00	0.98	0.98	0.99	0.99	1.00	0.99	0.98							
2002	0.97	0.97	1.00	0.97	0.96	0.98	0.90	0.97	0.96	0.96	0.98						
2003	0.99	0.98	1.00	0.99	0.98	0.99	0.97	0.98	0.99	0.98	0.99						
2004	0.97	0.98	1.00	0.94	0.97	1.00	0.99	0.97	0.98	0.96	0.98	0.93	1.00				
2005	0.99	0.98	1.00	0.99	0.99	1.00	0.98	0.98	0.99	0.98	0.98	0.99	1.00	0.97			
2006	0.98	0.98	1.00	0.99	0.99	1.00	0.98	0.97	0.99	0.99	0.97	0.99	1.00	0.98			
2007	0.98	0.98	1.00	0.95	0.98	1.00	0.97	0.97	0.99	0.97	0.98	1.00	1.00	0.98			
2008	0.96	0.98	1.00	0.97	0.99	0.99	0.98	0.98	0.99	0.98	0.97	0.98	1.00	0.97			
2009	0.96	0.98	0.96	0.96	0.97	0.96	0.98	0.98	0.96	0.96	0.97	0.93	0.86	0.97			
2010	0.99	0.98	1.00	0.99	0.99	1.00	0.97	0.98	0.99	0.99	0.98	0.93	1.00	0.95			
2011	1.00	0.98	1.00	0.99	0.99	1.00	0.99	0.98	0.98	0.99	0.98	0.95	1.00	0.97	0.97		
2012	0.98	0.97	1.00	0.97	0.96	0.98	0.99	0.98	0.96	0.97	0.98	0.97	1.00	0.98	0.96		
2013	0.98	0.98	1.00	0.97	0.98	0.98	0.99	0.98	0.98	0.94	0.99	0.98	1.00	0.98	0.98	0.98	
2014	1.00	0.98	1.00	0.99	1.00	1.00	0.99	0.98	0.99	0.99	0.98	0.99	1.00	0.98	0.98	0.99	
2015	0.98	0.97	1.00	0.98	0.98	0.98	0.99	0.98	0.98	0.98	1.00	0.96	1.00	0.98	0.94	0.95	
2016	0.91	0.96	1.00	0.92	0.91	0.92	0.97	0.98	0.92	0.92	0.99	0.98	1.00	0.97	0.97	0.96	
2017	0.96	0.98	1.00	0.96	0.94	0.96	0.98	0.99	0.95	0.96	0.99	0.96	1.00	0.99	0.96	0.95	
2018	0.98	0.98	1.00	0.98	0.98	0.98	0.98	0.99	0.98	0.98	0.98	0.96	1.00	0.97	0.94	0.88	
2019	0.91	0.97	1.00	0.91	0.93	0.92	0.98	0.98	0.92	0.89	0.99	0.97	1.00	0.98	0.97	0.95	0.96
2020	0.86	0.92	1.00	0.87	0.86	0.87	0.97	0.95	0.88	0.87	0.95	0.97	1.00	0.92	0.97	0.96	0.97
2021	0.87	0.97	0.98	0.92	0.93	0.88	0.98	0.98	0.95	0.90	0.99	0.98	1.00	0.93	0.98	0.98	0.98
2022	0.96	0.98	1.00	0.95	0.93	0.96	0.98	0.98	0.95	0.95	0.99	0.98	1.00	0.90	0.97	0.98	0.97
2023	0.85	0.96	1.00	0.89	0.92	0.85	0.97	0.96	0.92	0.87	0.97	0.94	1.00	0.88	0.93	0.94	0.93
2024	0.92	0.95	1.00	0.92	0.92	0.93	0.93	0.97	0.94	0.92	0.98	0.93	1.00	0.94	0.94	0.93	0.90
2025	0.97	0.97	1.00	0.97	0.95	0.97	0.97	0.97	0.96	0.97	0.98	0.97	1.00	0.89	0.96	0.97	0.96

Note: MET=METED, PEP=PEPCO, PEN=PENELEC, PEP=PEPCO, COM=COMED and OVE=OVEC zones

5. Data

Our analysis relies on an extremely rich data set for the PJM market extending back over 20 years and including more than 25 million hourly nodal prices. Hourly DA LMP price data was obtained from June 2000 to June 2025 from GridStatus.io and PJM. Daily gas price data was obtained from Bloomberg, based on published ICE spot prices at various gas trading hubs within the PJM footprint.

Capacity prices were obtained from PJM. It should be noted that prior to 2008 capacity prices in PJM did not vary by locations within the market and hence provided no locational pricing signal. SREC prices were sourced from the PJM Generation Attribute Tracking System (GATS) database by state and year.

Data on new generation plants built in PJM was obtained from the U.S. Energy Information Administration Form 860 data (EIA, 2025). We rely on plant level investment data rather than unit level data, as the investment decision for multiple unit plants (for example within a combined cycle gas turbine (CCGT) plant, for example, the dominant form of entry over much of the period) would typically be made on a plant, rather than unit basis.

We analyze investments in large plants (greater than 1 MW in installed capacity). These make up a significant fraction of total additional capacity and are subject to PJM's large generator interconnection agreement. There are many more small units, but many of these are small solar and cogeneration projects for which the locational investment decision is likely to be more tied to individual circumstances (such as on-site industrial loads) than market prices. We exclude all units in the EIA generating dataset identified as cogeneration/combined heat and power (CHP) for the same reasons.

In total, our data set includes over 1100 units added in regions that were part of the PJM market at least 2 years before the plant entered service. This includes 938 solar photovoltaic plants totaling 14.4 gigawatts (GW), 101 wind farms totaling 10.8 GW and 127 thermal plants totaling 81.5 GW. Most thermal units (such as combustion turbines (CT) and CCGT plants) have more than one unit but are treated as a single plant for purposes of our investment analysis since these will reflect a single investment decision.

An issue in analyzing the LMPs associated with new entry is that most new large generating plants will have a new pricing node (pnode) established at the grid point where the plant delivers power into the grid. There are therefore generally no historical LMPs visible at that specific pricing node until the plant begins operation.

From a data perspective, there are multiple potential estimation solutions to this problem. Investors in new generation will often use power flow modeling to assess local transmission constraints to evaluate the potential mean basis between the new pricing node and a well-established hub or zonal price for which data is available. Since these hub and zonal prices are much more traded than individual nodal prices, this ties the forecast of future plant LMPs to traded prices, where some level of price discovery may exist. Such power flow modeling is not feasible for an analysis of this scale, however, and would require extensive non-public engineering data.

Another approach is to estimate the future pricing node LMP in reference to an existing pricing node for which there are available historical prices. Brown *et. al.* use geographically close LMPs to establish a proxy price for new generation decisions (Brown, Zarnikau and Woo, 2020). A limitation here is that LMPs reflect transmission constraints on the grid, and not locational geography. Nearby generators connected on different lines at different voltages may have a larger variation in LMPs than distance might suggest.

We use nearby prices at geographically close existing nodes as a proxy for LMP at the new generator node. Most new generators are within a few dozen miles of a corresponding proxy node. We test to ensure that throughout the period, historically observed proxy prices are consistent with the observed out-turn LMPs, to confirm statistically that it would be reasonable for investors to rely on these historical prices in estimating future nodal LMPs where generation would be built. These results are presented in the Annex.

6. Descriptive Statistics on Generator Investment

Before presenting our econometric analysis of generation investment in PJM over this period, in this section we examine patterns of generation investment and related prices to explore how these interact over time.

Table 2 shows provides some basic statistics on investment in the PJM region since 2000. PJM currently has an installed capacity of approximately 200 GW, with approximately half of this capacity constructed since 2000.[14] All of the baseload nuclear and most of the coal capacity was built before 2000. Since 2000, new capacity has mostly been natural gas-fired (primarily CCGT), wind and solar.

Table 2 PJM Generating Capacity Additions (MW) by Period and Technology

Period	Coal	Gas CCGT	Gas CT	Wind	Solar	Other
2000-2004	585	18,406	21,559	268	-	706
2005-2009	659	1,356	863	3,014	27	178
2010-2014	1,476	4,860	686	3,375	632	428
2015-2019	-	23,371	588	2,550	2,545	555
2020-2024	-	9,249	380	2,216	11,414	316
Total	**2,719**	**57,241**	**24,076**	**11,423**	**14,617**	**2,183**

PJM has over 2200 individual generating plants, but many are small. As discussed previously, we do not include small units in our analysis below (less than 1 MW) as these are likely connected to individual loads and hence are less likely to be influenced by LMPs or other locational prices with respect to siting. We explicitly exclude units identified by EIA as cogeneration/CHP units. Excluding small and cogeneration units leaves over 1200 units in our dataset of investments in plants.

6.1. Solar generation

New solar PV facilities have made up most new generation in PJM by number of units over the last two decades, comprising over 75% of all new plants more than 1.0 MW. New Jersey saw significant investment in new PV capacity after 2010, significantly driven by state policies and SREC prices (as seen in **Figure *6***), although many of these facilities were small. More recently the Dominion zone in Virginia has been the location of most new PV capacity.

Solar plants in PJM see three different locational price signals: nodal LMPs, zonal capacity prices and state-level REC prices.[15] In this section we examine whether higher prices influence entry decisions using descriptive statistics.

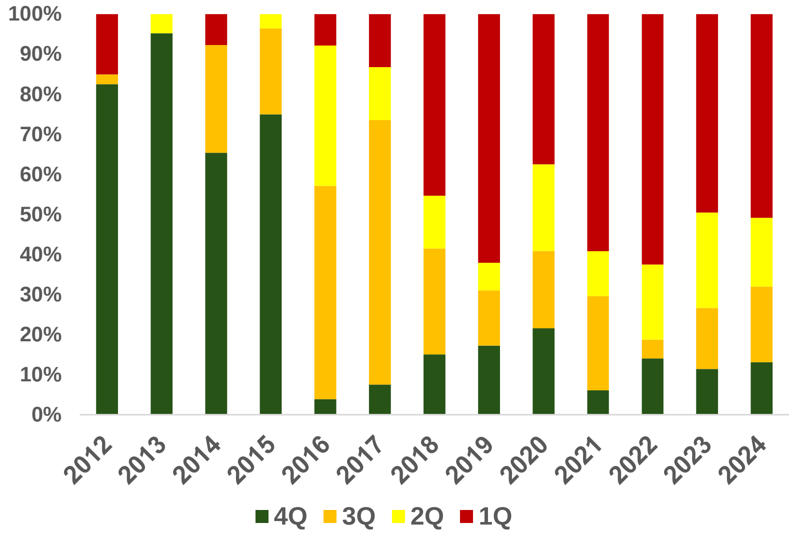
[14] The first line of Table 1 includes units in PJM which have been mothballed and which are not bid into the recent capacity auctions, but which could return to service in theory at least.

[15] New generators also face interconnection costs which may vary by location, but these are fixed for each plant and are not directly observable.

6.1.1. *Solar investment and LMPs*

LMPs tend to be higher in eastern PJM along the Atlantic coast, where load and natural gas prices (in high gas demand periods in winter) tend to be higher. Figure 7 shows the share of new solar capacity (in terms of new plants greater than 1 MW) by year from 2012 to 2024 by LMP quartile, so that the 4th quartile represents entry in the highest priced locations and 1st quartile represents the lowest priced locations.[16] Given the time between when an investment decision is made and when the PV plant can start operations, the LMPs are lagged by two years. The LMPs used reflect daylight hours only ("solar hours") to reflect prevailing nodal prices when a solar PV plant would be generating. In our econometric analysis we account for the variation in potential solar output by location as a driver in locations of new PV plants.

Figure 7 Share of new solar facilities by solar hours LMP quartile (lag 2 years)



As can be seen, initially most new PV entry occurred in high LMP locations. Over time, as the number of new PV plants has grown dramatically, entry has become more spread across the PJM market. This is also consistent with the general sharp decline in PV costs over the period 2012 to 2024 (Lazard, 2025).[17]

6.1.2. *Solar generation and capacity prices*

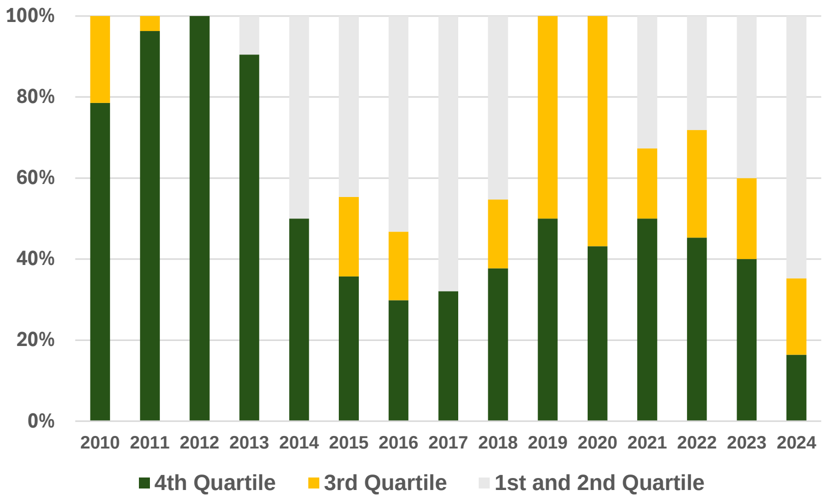
Figure 8 provides a similar view of new solar entry by quartiles of zonal capacity prices, with again the 4th quartile representing the highest zonal prices. Initially new PV plants were almost all in the highest priced zones in eastern PJM but have spread over time to much of the PJM region.[18]

Figure 8 Share of new solar facilities by zonal capacity price (lag 2 years)

16 If PV entry was independent of lagged LMP prices we would expect to see approximately 25% of entry in each year in each of the quartiles, creating a series of equal sized green, orange, yellow and red bars. The quartiles represent investment locations in a year over all locations where investment occurred in all years. This constrains the analysis to locations where new generation is demonstrably possible and hence excludes many of the highest LMP locations (such as in an around major cities) where new build generation may be impractical.

17 For the renewable technologies in our sample (solar and wind) we focus these descriptive statistics on the period 2012 to 2024 as there were only a relatively small number of units added before 2012.

18 Since PJM capacity prices are zonal, and many lower-priced zones often clear at the same price given the auction format, there is typically little or no difference between 1st and 2nd quartile capacity prices in a year. These have therefore been combined in Figure 8.



6.2. Wind Generation

Our sample includes over 100 new wind farms greater than 1.0 MW. New wind entry in PJM has been concentrated in a few regions: the northern Appalachian Mountains, Indiana and northwestern Ohio, and northern and central Illinois. These are generally not regions associated with high LMPs or zonal capacity prices in PJM. However, these locations in Illinois, Indiana and Ohio reflect regions with high average wind speeds at 80 meters height, a standard measure of wind potential (NREL, 2025).

Figure 9 shows the share of new wind farms by quartile of all hours lagged LMPs (lagged two years), as was presented above for solar units. This confirms that few new wind farms have been built in high LMP locations in PJM.

Figure 9 Share of new windfarms by all hours LMP quartile (lag 2 years)

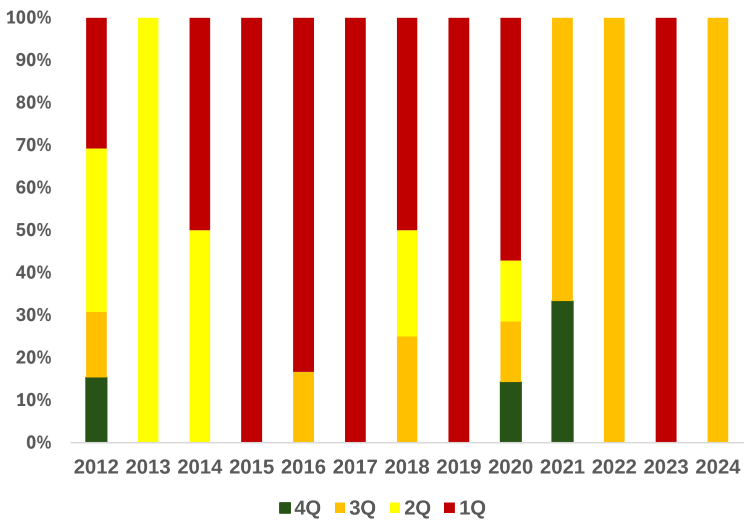
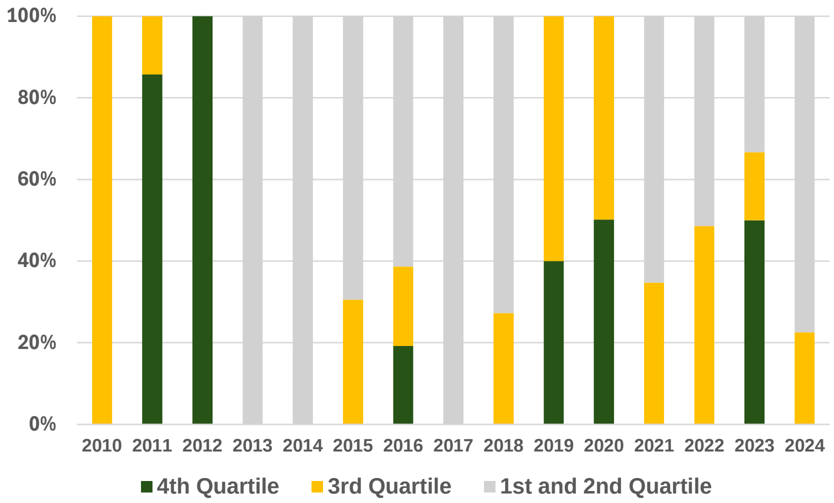


Figure 10 shows entry based on quartiles of zonal capacity prices. Only in the first few years was entry concentrated in higher capacity price zones. Note that the number of windfarms added in most years is relatively small so share statistics are volatile.

Figure 10 Share of new windfarms by zonal capacity price quartile



Unlike solar generation, where new entry has been more concentrated in high LMP and capacity price zones on average, new wind generation in PJM has been concentrated in a handful of regions where both energy and capacity prices are generally below the PJM average. These results show that specific locational effects related to wind resource (which can vary substantially even over relatively short differences) outweigh locational benefits of higher energy and capacity prices.

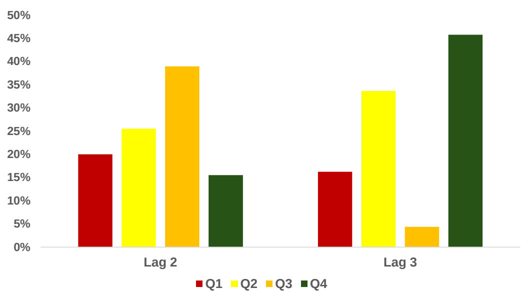
6.3. Gas-fired Generation

PJM has added over 81 GW of new gas-fired generation since 2000, primarily CCGTs. This is made up of 114 major new plants (over 400 new individual generation units) and excludes units listed as being cogeneration/CHP units as well as units smaller than 1.0 MW. As was seen in Table 1, new gas generation was concentrated in the periods from 2000 to 2004 and from 2015 to 2018.

6.3.1. Gas generation investment and LMPs

Most CCGT operating hours, and nearly all CT operating hours are in peak hours in PJM, when demand and prices are higher.[19] Figure 11 shows the share of new CCGT generation entering the market by average peak hour LMPs lagged by two or three years.

Figure 11 Share of new CCGT generation by peak hour LMP quartiles



6.3.2. Investment and historical margins

It might be expected that new investment decisions would be based not on historical LMPs but on margins. CCGT margins by location within PJM can vary significantly based on the relationship between clearing hourly peak LMPs and (daily) local gas prices.

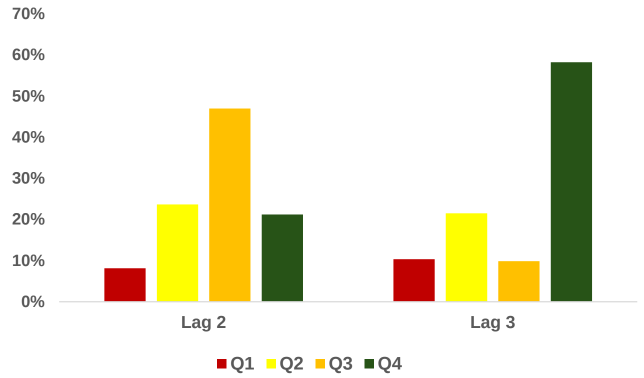
[19] PJM defines peak hours as being from hour ending 8:00 to hour ending 23:00 Eastern prevailing time for weekdays.

Annual margins for years *t* were estimated at generator locations (subscripted *i*) as:

$$Marg_{i,t} = \sum_{h=1}^{8760} LMP_{i,h} - HR_t Pgas_{i,h} - VOM \qquad (4)$$

Gas prices are daily and were treated as constant over each hour in a day.[20] The average heat rate and variable operations and maintenance costs (VOM) for a new CGGT were based on averages used in PJM's capacity market cost of new entry (CONE) calculations.

Figure 12 Share of new CCGT generation by lagged CCGT margin quartiles

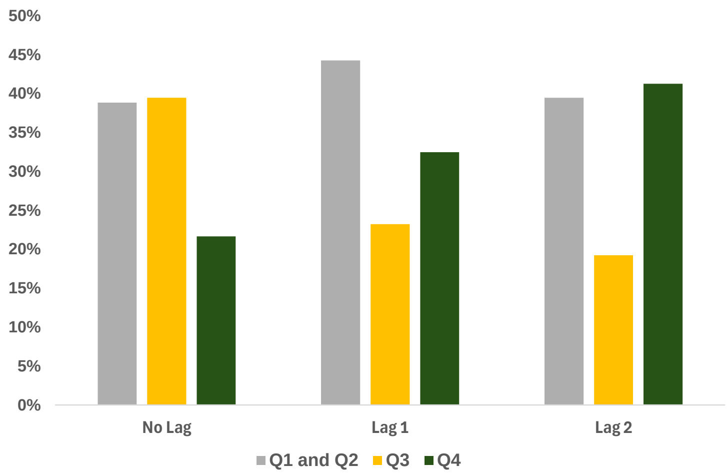


Entry was concentrated in the highest margin quartiles (quartiles 3 and 4) when examining prices 2 or 3 years before a CCGT plant started operations.

6.3.3. Investment and capacity prices

For our gas entry analysis reflecting capacity prices, we start in 2009 as capacity prices were not locational in PJM until 2007. Figure 13 shows the share of new gas generation entry (combining CCGT and CTs) for 2009 to 2024 by capacity price quartiles at various lags. Capacity prices lagged by two years show the highest percentage of entry in the top quartile of (zonal) capacity price regions.

Figure 13 Share of new gas generation 2009-2024 by capacity price quartiles



20 U.S. gas markets do not trade day-ahead on weekends and certain holidays. Prevailing prices over these gas flow days were used in estimating margins for these days.

Interpreting capacity price lags in PJM is complex as capacity prices are set in auctions which clear before the year in which capacity revenues are paid. The RPM capacity market design envisioned auctions held in advance to allow new entrants to participate, but in practice the timing of forward auctions has not always been constant (especially in the early years of the RPM capacity market). Delays in recent auctions have made the time between when auction prices are set (observable to an investor) and when the plant enters service variable.

7. Econometric analysis of generation investment decisions

In an earlier section, we develop a model of generation investment which recognized that investors will be forward-looking when considering LMPs and other prices that affect generation revenues but also recognized two salient features of any investment decision. First, investor expectations are private. While there is some forward trading at a few hubs in PJM and other electricity markets, liquidity is limited more than a few years out. Traded forwards and futures are also unlikely to be available at any specific location, so it is not possible for generators to make locational investment decisions based solely on visible market data. Second, since the price uncertainty over the life of a generation asset is so uncertain, most new generation investment in PJM (and other LMP markets) is based on offtake contracts or hedges which help stabilize generator revenues for considerable periods, often a substantial portion of a new generation asset's total economic life. Given these realities, the location decision for new generation depends on the ability of generators and offtake counterparties to form reasonable expectations over price differences between potential generation pricing nodes and locations where sales or hedging occurs, since one party or another must absorb this locational basis risk.

In this section we use two strategies to analyze patterns of generation investment and the influence of locational energy and capacity prices on these decisions. Since the private expectations of generation investors are not observable, we test whether past energy and capacity prices (which would have been available to all investors) are significant in terms of where new generation was located. In the second strategy, we analyze whether it was possible for investors to form reasonable projections of locational differences between prices at local nodes and trading hubs where much hedging occurs, given only past prices.

7.1. Historical energy prices as signals for new entry

The simplest model of future prices is that long-term prices (and price differentials) can be estimated from current prices at the time the investment decision is made (e.g., several years before the generating plant enters services).

In this section we apply logistic panel regression to test if generation investment in PJM is related to historic LMPs, capacity prices and other variables relevant to specific forms of generation investment (such as the SRECs discussed above for solar PV plants, and margins for gas-fired generation such as CCGTs and CTs). Given the timing of investment decisions versus operational dates for plants, as discussed previously, we primarily rely on lagged pricing variables.[21]

Modelling investment decisions at specific location *i* was performed using logistic panel regression. Given the differing expected drivers of investment for different types of generation, we analyze investment in solar, wind and gas-fired generation separately, but relying on the same basic model form.

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21 The relative contribution of LMP and capacity prices towards net revenues needed to support investment varies by technology type. Gas-fired CT peakers rely predominantly on capacity market revenues on average, while the relative net revenue contribution of wind and solar is substantially lower, as the ELCC for these resources is typically much lower.

Consider a model in which the probability of a generation investment at location *i* is defined by the logistic function:

$$P_i = \frac{1}{1+e^{-Z_i}} \qquad (5)$$

Z_i is defined as a variable described by a vector of coefficients and covariates ***x:***

$$Z_i = \boldsymbol{\beta x} \qquad (6)$$

The probability of an event (e.g. investment at location *i*) not happening is:

$$1 - P_i = \frac{1}{1+e^{Z_i}} \qquad (7)$$

The odds-ratio of the event is the ratio of the probabilities so:

$$\frac{P_i}{1-P_i} = \frac{1+e^{Z_i}}{1+e^{-Z_i}} = e^{Z_i} \qquad (8)$$

Taking the natural log of both sides leads to

$$ln\left(\frac{P_i}{1-P_i}\right) = z_i = \boldsymbol{\beta x} \qquad (9)$$

The logistic panel model can be generally written as:

$$L_{i,t} = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 x_{i,t}^1 + \beta_2 x_{i,t}^2 + \varepsilon \quad (10)$$

While the structure of the logistic model is simple, the interpretation of the coefficients on the regressors is more complicated. A coefficient β in a logistic regression does not represent the direct marginal effect of a change in the regressor (as in a standard linear regression) but reflects the change in the log-odds from a given probability level as the underlying specification is of a cumulative distribution function and hence a change depends on the probability level from which the change is measured.

The marginal effect on probability from a change in a dependent variable in **x** depends on each of the variables in **x**. The relative marginal effect between two variables, as expressed as the ratio of two coefficients, does not depend on the initial probability (Wooldridge, 2002). We will use this in examining the relative impacts of different price inputs later in our analysis.

Logistic panel models in general may suffer from all the usual issues affecting panel data including non-stationarity, serial correlation, etc. These issues will be addressed in the following sub-sections dealing with model specifications and results for each of the investment types analyzed (solar, wind and thermal generation technologies). Given that we use test generation investment against annual historical mean LMPs, we account for the substantial cross-sectional shocks affecting all LMPs using yearly dummies, which allows the remaining LMP variation to reflect basis differentials between different pricing nodes in the year when a generation investment is made.

7.2. Solar generation

The basic specification of the log-odds solar investment logistic regression is:

$$L_{i,t} = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 LMP_{i,t-k} + \beta_2 CapPrice_{i,t-k} + \beta_3 SREC_{i,t-k} + yeardummy_t + \varepsilon \qquad (11)$$

In this and the other models *k* represents potentials lags where *k*=[0,1,2,3]. We primarily focus on a measure of average LMPs during daylight hours ("solar LMPs") as more reflective of prices received by PV generation.

The PJM region is large with significant variation in solar PV output across the market footprint. We used latitude-longitude data for specific locations to estimate solar output by generation location from the Global Solar Atlas.

Since potential solar output by location is assumed to be time-invariant, it will not affect regression outputs in the fixed effect logistic panel specification. To account for solar output variation in the fixed effects setting, we define a new variable related to potential solar revenues (*solarrev*) which is the product of the locational LMP adjusted by an index of mean locational solar output. This is used in some specifications in place of the basic lagged mean solar LMP regressor, providing the model specification in equation 12 below.

$$L_{i,t} = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 solarrev_{i,t-k} + \beta_2 CapPrice_{i,t-k} + \beta_3 SREC_{i,t-k} + yeardummy_{i,t} + \varepsilon \quad (12)$$

7.2.1. Model estimation

In this section we describe model estimation issues in detail for the solar investment panel regression; similar estimation issues were also encountered for the wind and gas-fired generation segments.

LMPs, capacity and SREC prices are strongly correlated across panels as prices (LMPs especially) are highly correlated across the PJM market. This introduces significant cross-panel correlation as each panel is subject to the same time-dependent shock related to underlying changes in market prices, as demonstrated using the Pesaran CD test for cross-sectional dependence, which can be used when the number of panels *N* is large in comparison to the number of time periods *T* , as is the case here (Pesaran, 2004). The CD test for all three independent variables in equation 7 shows strong cross-section dependence, related to highly correlated price shocks across locations. To address this, we introduce a time period dummy *yeardummy* to account for cross-sectional shocks at the yearly level.

Since the number of panels *N* is substantially larger than the number of time periods *T*, we used the Harris-Tzavalis test for unit roots in the price series. The test statistics strongly rejected the hypothesis of unit roots in the relevant price series.

Even with the time period dummy, significant serial correlation can exist in panel data sets. The Wooldridge test confirmed significant serial correlation in the price series, as expected. To account for the presence of significant serial correlation, we report cluster-robust standard errors in our analysis of coefficient significance.

All models were estimated using maximum likelihood. To test the impact different lags in the relevant price data on the binary investment decision *Inv*, we ran logit models across the set of different potential lags and report the model with lags which minimized the Aikaike information criterion (AIC) and Bayesian information criterion (BIC). In general, the log-odds coefficients and signs were largely consistent across the various lags considered. These are then compared to the lagged price results in the descriptive statistics analysis provided previously.

7.2.2. Model results

Logistic regression results for some different model specifications are presented in Table 3 below. Analysis of different lags shows that the AIC and BIC were generally minimized with a lag of three years on LMP-related prices (all hours LMPs in (1), peak hour LMPs (2), solar hour LMPs (3) and the *solarrev* variable discussed previously in (4)). The results using each of these inputs were similar, although the *solarrev* parameter, which accounts for potential output differences by location, performed very slightly better than the others.

Table 3 Logistic regression results - solar

(1)			(2)			(3)			(4)		
LMP	0.0736	***	**Peak hour LMP**	0.0685	***	**Solar hour LMP**	0.0766	***	**solarrev**	0.0794	***
(lag 3 years)	(0.0168)		*(lag 3 years)*	(0.0139)		*(lag 3 years)*	(0.0143)		*(lag 3 years)*	(0.0138)	
CapPrice	0.0034	**	**CapPrice**	0.0031	**	**CapPrice**	0.0027	**	**CapPrice**	0.0026	*
(lag 2 years)	(0.0013)		*(lag 2 years)*	(0.0014)		*(lag 2 years)*	(0.0013)		*(lag 2 years)*	(0.0014)	
SREC price	0.0047	***	***SREC price***	0.0047	***	***SREC price***	0.0047	***	***SREC price***	0.0047	***
(lag 3 years)	(0.0006)		*(lag 3 years)*	(0.0006)		*(lag 3 years)*	(0.0006)		*(lag 3 years)*	(0.0006)	
yeardummy	yes		***yeardummy***	yes		***yeardummy***	yes		***yeardummy***	yes	
LR Chi-2	253.4			258.4			263.39			268.1	
Number of obs.	9.796			9.796			9.796			9.796	
AIC	3842.2			3836.9			3831.9			3827.2	
BIC	3942.9			3937.6			3932.6			3928.0	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05 and * p<0.10

The optimal capacity price lag was two years. It should be remembered, however, that capacity prices are set in auctions in PJM before the delivery date, so this capacity price translates to an effective lag time of approximately three or more years before the reported PJM operational date.[22] SREC prices show an optimal lag time of three years as well, although the variation was slight.

The optimal lag of three years on LMPs and *solarrev* appears broadly consistent with the approximate timing necessary to finance and build a utility-scale solar PV project, given that project siting choices would have to be made ahead of closing the financing, site preparation works and installing the PV panels and associated other facilities.

7.2.3. Interpreting marginal effects from logistic regressions

Interpreting logistic regression results is more complex than in the basic OLS format. First, the coefficient in the logistic regression model (per equation 10) is the coefficient on the log of the odds ratio, not the probability. Second, unlike in a linear model, the marginal effect in a logistic regression depends on the current probability value. A common way to express the results of a logistic regression is via average marginal effects, which shows the marginal change in probability from a unit change in each regressor at the average level of all regressors.

For Model 1 in Table 3, the average marginal effect of the LMP, capacity price and the SREC price are 0.0000679, 0.0000024 and 0.0000041 respectively. This represents the average increase in probability of an investment at node *i* (across all period and sample values) from a unit change in the relevant price. The probabilities are necessarily small here as by model definition there is only a small chance of an investment in each period at one of almost 1000 nodes. Normalizing by the number of (solar) nodes where investment occurred gives normalized marginal probability effects of 6.4% for a unit change in the LMP (e.g., $1/MWh), 0.2% for a unit change in the capacity price ($1/MW-day) and 0.4% for a unit change in the SREC price ($1/SREC).

The ratio of the marginal probability effect of the LMP to the capacity price is approximately 27.7. However LMPs and capacity prices are in different units. For a solar project with a 20% capacity factor on average, a $1/MWh change in LMP represents approximately $1,752 in marginal revenue per megawatt of capacity.[23] For capacity prices, the marginal revenue must reflect the percentage of solar capacity counted in the capacity market. Current ELCC's for fixed and tracking solar plants in PJM range from 7-8% of installed capacity.[24] Before the ELCC method was implemented, however, the effective capacity credit (based on availability in summer peak hours) was substantially higher. Assuming a 20% capacity credit (on a capacity weighted-average basis) leads to marginal capacity revenue associated with a $1/MW-day increase in local capacity price of $73/MW-year (=$1/MW-day * 365 days/year * 20%). The ratio in the marginal revenues of a unit price increase is ($1752/MW-year/$73/MW-year ≈ 24. This is generally consistent with the marginal probabilities discussed (ratio ≈ 27.7). The marginal probabilities calculated from the logistical regression are thus generally consistent with the marginal revenue contributions of LMPs and capacity prices to solar project revenues. Since SRECs are denominated in MWh, the marginal contribution of SRECs should be much higher than capacity prices but the marginal

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22 As explained previously, the timing of PJM Base Residual Auctions for the capacity market have varied over time, so there is not a single fixed lag value associated with the capacity price parameter in all years.

23 Calculated as 8760 hours/year * 20% * $1/MWh =$1,752/MW-year.

24 These are the ELCC values from the 2027/28 base residual auction.

effect is only slightly higher. This result indicates that generation investors place less weight on SREC prices, which are dependent on state regulation and highly volatile.

7.3. Wind generation

The wind generation investments in the period include 101 individual wind farms, which were concentrated in a few regions of the PJM market, especially Indiana, northern Illinois and ridges in the Appalachian Mountains. These regions also largely correspond with the highest mean wind speeds.

7.3.1. Wind model specification

The basic function form of the wind investment logistic regression is shown in equation 13; this is similar to the solar regression model without the SREC price term. Similar estimation procedures were used including robust standard errors and year dummy variables to account for cross-sectional dependence at the yearly level.

$$L_{i,t} = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 LMP_{i,t-k} + \beta_2\, CapPrice_{i,t-k} + yeardummy_t + \varepsilon \quad (13)$$

We also define a parameter *windrev* which is the LMP scaled by an index of potential wind output at the location. The index was calculated from mean wind speeds at each project location from the Global Wind Atlas (Global Wind Atlas, 2025). We note that mean wind speeds, especially in the mountainous Appalachian regions, varies substantially over relatively short distances, unlike the solar variability used in the *solarrev* parameter.

$$L_{i,t} = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 windrev_{i,t-k} + \beta_2 CapPrice_{i,t-k} + yeardummy_{i,t} + \varepsilon \quad (14)$$

7.3.2. Model results

Logistic regression results for the wind models are presented in

Table 4. Investment in wind farms does not appear to be affected by lagged LMPs or capacity prices. This is also true for the *windrev* variable which attempts to account for potential wind resource variation by project location.

Table 4 Logistic regression results - wind

(1)		(2)		(3)		(4)	
LMP	-0.0768	**LMP**	0.0916	**LMP**	0.0786	**windrev**	-0.0919
(lag 3 years)	(0.1100)	*(lag 2 years)*	(0.0655)	*(lag 1 year)*	(0.0580)	*(lag 2 years)*	0.1129
CapPrice	0.0052	**CapPrice**	-0.0005	**CapPrice**	-0.0007	**CapPrice**	0.0055
(lag 2 year)	(0.0103)	*(lag 1 year)*	0.0079	*(lag 2 years)*	(0.0076)	*(lag 2 years)*	(0.0103)
yeardummy	yes	***yeardummy***	yes	***yeardummy***	yes	***yeardummy***	yes
LR Chi-2	14.3		30.73		34.51		14.49
Number of Obs.	467		675		853		467
AIC	205.4		263.9		317.1		205.2
BIC	259.2		327.1		388.5		259.1

Robust standard errors in parentheses
*** p<0.01, ** p<0.05 and * p<0.10

7.4. Gas-fired generation

The basic specification of the log-odds gas-fired generation investment logistic regression is provided in equation 10. Other than the different regressors used, the estimation process was like that used for solar generation.

$$L_{i,t} = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 LMP_{i,t-k} + \beta_2 CapPrice_{i,t-k} + yeardummy_{i,t} + \varepsilon \quad (15)$$

We also estimate a logistic regression model using the "LMP margin" as a lagged dependent variable. The LMP margin for each location and year is calculated on an annual basis using equation 11. LMP margins were calculated separately for CCGT and CT plants but margins were pooled in a single regression.

$$L_{i,t} = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 lmp\_marg_{i,t-k} + \beta_2 CapPrice_{i,t-k} + yeardummy_{i,t} + \varepsilon \quad (16)$$

Capacity prices in PJM were not location-based until 2007 and did not show significant locational variation until 2008. Given the sparseness of thermal generation investments in this period, the gas logistic model was estimated using data from 2010 to 2024.

7.4.1. Model results

Logistic regression results for gas-fired generation against historic LMP prices and margins are shown in Table 2. Investment at individual nodes was significantly related to local LMPs and LMP margins with a three-year lag, but with declining or no significance at shorter lags. Lagged capacity prices were significant across the models.

Table 5 Logistic regression results – gas-fired generation

(1)			(2)			(3)			(4)			(5)		
LMP	0.2307	***	**Peak hour LMP**	0.2059	***	**Imp_marg**	0.2761	***	**Imp_marg**	0.1715	**	**Imp_marg**	0.0496	
(lag 3 years)	(0.0813)		*(lag 3 years)*	(0.0672)		*(lag 3 years)*	(0.0832)		*(lag 2 years)*	(0.0809)		*(lag 1 year)*	(0.0618)	
CapPrice	0.0133	***	**CapPrice**	0.0131	***	**CapPrice**	0.0130	***	**CapPrice**	0.0111	**	**CapPrice**	0.0117	**
(lag 2 year)	(0.0050)		*(lag 1 year)*	(0.0051)		*(lag 2 years)*	(0.0050)		*(lag 2 years)*	(0.0053)		*(lag 2 years)*	(0.0049)	
yeardummy	yes		***yeardummy***	yes		***yeardummy***	yes		***yeardummy***	yes		***yeardummy***	yes	
LR Chi-2	54.97			56.46			57.87			51.72			45.92	
Num, of Obs.	647			647			647			654			674	
AIC	216.4			214.9			213.5			221.4			232.9	
BIC	288			286.5			285.1			293.1			305.1	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05 and * p<0.10

These results appear consistent with the quartiles analysis in the previous section, where the share of new plants in the highest LMP and capacity price quartiles was the largest at lags of two and three years respectively.

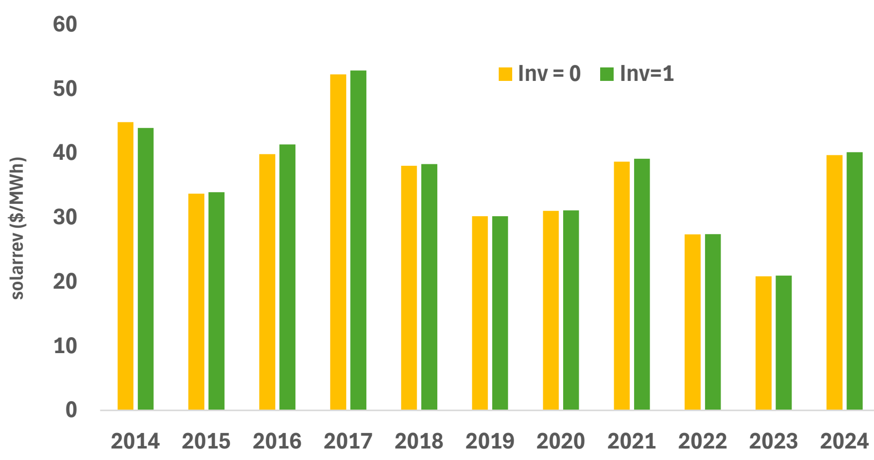
8. Investment impacts of intrazonal LMP differentials

The quartiles and logistical regression analysis presented previously examined generation investments across the PJM market, a large area with moderately large and persistent interzonal price differentials. However, it provided little insight into whether LMPs are significant in investment decisions within a zone.

To address this issue we examine solar investments in the Dominion zone in PJM, which have all occurred since 2012. There have been 211 new solar facilities built in the Dominion zone since 2014, making it the largest concentration of new build plants of a single technology in our data set of over 1100 new plant investments.

Looking at the locations in Dominion where PV investment has occurred, there is a slight but highly persistent bias in investing in regions with higher LMPs and predicted solar revenues (defined as before as the mean LMP during solar operating hours multiplied by a solar irradiance index). Figure 14 shows the lagged (three years) annual mean *solarrev* parameter for locations with (green column) and without (yellow column) in that year. Although the price differentials are slight, in each of the 11 years LMPs and *solarrev* were higher in locations where investments were made.

Figure 14: Mean *solarrev* parameter (lagged 3 years) conditional on investment decision



Intrazonal price impacts may also be tested econometrically using the logistical regression approach previously developed, but this time limited to PV plants within the single Dominion zone. In this case the model specification must exclude capacity prices and SREC prices as these are all the same within the same zone/state and hence completely collinear. This leaves the model specification shown in equation 17 below, where *solarrev* may replaced by LMPs, peak hour LMPs and so on.

$$L_{i,t} = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 solarrev_{i,t-k} + yeardummy_{i,t} + \varepsilon \qquad (17)$$

Fitting this model to the 211 investments made since 2014 shows that lagged LMPs and LMP-derived parameters such as *solarrev* are significant with respect to investment location for PV facilities within the Dominion zone.

Table 6 Intrazonal investment regression results

(1)			(2)			(3)			(4)		
LMP *(lag 2 years)*	0.1512 (0.0407)	***	**Peak LMP** *(lag 2 years)*	0.1255 (0.0334)	***	**Solar LMP** *(lag 2 years)*	0.1488 (0.0366)	***	**solarrev** *(lag 2 years)*	0.1450 (0.0344)	***
Yeardummy	yes		**Yeardummy**	yes		**Yeardummy**	yes		**Yeardummy**	yes	
Number of Obs.	2532			2532			2532			2532	
AIC	1000.5			1000.4			998.7			997.8	
BIC	1070.5			1078.5			1068.7			1067.8	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05 and * p<0.10

These results suggest that intrazonal LMP differentials are important for locational investment decisions, at least for one region and one generation technology. It is difficult to generalize this analysis to other zones because no other zones have so much new build of a single technology, leading to a sparse data set on an intrazonal basis. However, the Dominion results suggest that intrazonal LMP differences, which are small but persistent, do affect investment decisions over the long run.

9. Analysis of basis differentials

Much of the overall uncertainty in PJM LMPs relates to volatility in the overall system marginal energy cost. This in turn reflects variability in natural gas prices (which vary across the region but are themselves highly correlated as was seen in Figure 3), weather and other drivers of electricity demand, and other factors.

Most new generating plants, especially the renewable assets that make up most new generating units in our PJM dataset, are built against offtake agreements that help stabilize revenues over the longer term, which are not predictable in detail. In this case, a natural question arises. Are electricity price basis differentials in PJM (which arise from differing congestion and marginal loss components by node) stable enough to allow generators and offtakers to form reasonable assumptions to contract, and to price these basis differentials in offtake contracts?

Since offtake prices, like investor expectations, are not public, we use a simple OLS framework to show that basis differentials relative to a small number of trading hubs are relatively predictable, even if overall LMPs are not. For a given node *i*, the regression below relates the LMP in a period (1 hour in the day-ahead market) to the trading hub LMP.

$$LMP_{i,t} = \beta_0 + \beta_1 HUB_{m,t} + monthdummy + \in \quad (18)$$

This regression is estimated using standard OLS and three years of hourly data for years [*y* to *y+2* inclusive] for the set of LMPs, with each LMP regressed against the most relevant hub price. For this analysis we use the set of zonal LMPs as a sample of the very large number of individual pricing node LMPs across the PJM region. The hub price for each zone is selected based on the hub with the highest correlation with the relevant LMP.

We use the individually estimated regression coefficients to forecast LMPs out-of-sample as a function of hub prices in the future. Since it will be some years from when an investment decision is made to when a generating plant enters service, we estimate the average LMP for five years over the years [over the years [*y+5,y+9*]. We then calculate the basis error on the out of sample prediction as a percentage of the out-term mean LMP at node *l* over the same five-year period, as shown in Equation 19 below.

$$BE_{\%} = \frac{\widehat{LMP_\iota} - \overline{LMP_\iota}}{\overline{LMP_\iota}} \qquad (19)$$

Table 7 below shows the percentage mean basis error for starting years *y* from 2005 to 2015, with prediction for the five-year periods starting in 2010-14 and ending in 2020-24. Given the overlapping time periods, the predicted error estimates are not independent.

Table 7 Percentage Predicted Basis Error 2005-2024

Zone	Estimation period	2005-07	2006-08	2007-09	2008-10	2009-11	2010-12	2011-13	2012-14	2013-15	2014-16	2015-17
	Prediction period	**2010-14**	**2011-15**	**2012-16**	**2013-17**	**2014-18**	**2015-19**	**2016-20**	**2017-21**	**2018-22**	**2019-23**	**2020-24**
AECO		-5.81%	-6.48%	-7.20%	-7.41%	-8.72%	-1.95%	-1.04%	-3.29%	-1.95%	-1.04%	-3.89%
BGE		0.88%	3.05%	7.71%	9.01%	8.38%	0.15%	-4.66%	4.80%	0.15%	-4.66%	-5.35%
DPL		-0.97%	-1.15%	-0.67%	-0.41%	-0.18%	1.05%	0.68%	1.39%	1.05%	0.68%	0.56%
JCPL		-2.59%	-6.64%	-11.65%	-10.85%	-9.48%	-2.73%	0.32%	-4.28%	-2.73%	0.32%	-1.79%
METED		-3.93%	-7.23%	-9.69%	-7.69%	-7.06%	9.68%	12.58%	4.97%	9.68%	12.58%	6.55%
PECO		-5.22%	-7.88%	-10.05%	-9.53%	-9.62%	-1.01%	0.22%	-2.11%	-1.01%	0.22%	-3.31%
PENELEC		3.53%	1.79%	-2.57%	-4.06%	-3.17%	-1.47%	0.98%	-3.66%	-1.47%	0.98%	1.96%
PEPCO		-2.34%	-0.62%	3.18%	5.39%	5.18%	-0.57%	-3.39%	3.21%	-0.57%	-3.39%	-3.47%
PPL		-4.09%	-6.83%	-9.18%	-7.73%	-7.55%	4.03%	6.54%	0.50%	4.03%	6.54%	1.98%
PSEG		-4.02%	-7.20%	-9.51%	-7.91%	-8.32%	-6.74%	-2.33%	-7.34%	-6.74%	-2.33%	-3.62%
APS		1.83%	0.32%	-4.17%	-3.67%	-2.39%	0.91%	-0.03%	1.42%	0.91%	-0.03%	-0.83%
AEP		9.92%	8.92%	3.09%	0.04%	0.18%	3.75%	2.96%	2.41%	3.75%	2.96%	3.10%
COMED		0.54%	0.39%	-0.07%	-0.27%	-0.24%	-0.19%	-0.11%	-0.30%	-0.19%	-0.11%	-0.16%
DOM		-5.32%	-6.40%	-3.03%	-0.77%	0.51%	4.18%	2.30%	3.54%	4.18%	2.30%	1.48%
Simple Mean		**-1.26%**	**-2.57%**	**-3.84%**	**-3.27%**	**-3.03%**	**0.65%**	**1.07%**	**0.09%**	**0.65%**	**1.07%**	**-0.48%**

As shown in the table, even a very simple OLS model can significantly predict the out-of-sample basis relationship between LMPs and hub prices years into the future. This suggests that although future LMPs are difficult to predict, reasonably predictable basis relationships provide sufficient stability to allow buyers and sellers to contract at hubs, with average energy price errors on the order of 10% or less. This has important implications for how new generation investment is made in LMP power markets.

10. Conclusions

A major claim for locational pricing has been that it can improve the efficiency of generation investment decisions, by directing investment to locations where new supply is more valuable. Despite this claim, there has been little empirical proof that investment decisions are significantly affected by LMPs. A previous analysis of the ERCOT market (relying on predicted future ERCOT LMPs) showed limited significance for LMPs in investment decisions.

Our analysis, using a much longer data set, suggests that historical LMPs are highly significant in shaping investment decisions. Our quartiles analysis shows that solar and thermal generation investments are significantly skewed towards locations with historical higher LMPs (and capacity prices). Our logistic regression results show that lagged historical LMPs and capacity prices are highly significant for investment in solar and thermal generation, but not for wind farms. This is likely due to high local variation in wind resources and siting issues associated with wind farms

Econometric analysis also shows that lagged LMPs are significant in locational decisions within a single zone, as evidenced by analysis of solar PV investments in the Dominion zone. Although LMP differentials within the zone are relatively modest, the logistical regression analysis showed that lagged LMPs were significant in locational investment decisions within the zone.

We do not expect that simple econometric models can predict LMPs over long periods, as these are driven by natural gas prices, demand growth, generation and transmission investment and many other factors. For this reason, we do not test actual investment decisions against predicted LMPs. This test places too much reliance on the reliability of econometric models to predict market behavior over long periods. Instead we note that many if not most generation investments are based on offtake contracts or other hedges, where basis risks between nodes are critical. Although LMPs are highly variable, our OLS analysis suggests that basis differences between LMPs and hubs are much more stable, and that even over substantial periods (out to eight years from the time an investment decision was made) that these basis differentials are typically under 10% of the out-turn LMP. This result is consistent with typical commercial hedging practice for many new generation investments, where offtake contracts and hedges are frequently settled at hub prices rather than individual generation node LMPs.

Our analysis has potential policy implications for jurisdictions considering LMP implementation. First, over long periods of time, generation investors do respond to locational price signals. This is not limited to LMPs, but also to zonal locational capacity and state-based subsidy prices. It appears that in PJM even relatively small solar facilities respond to price signals, which may be important for investments in this frequently decentralized technology.

Second, trading hubs where much of the volatility in future LMPs can be hedged are important. Our analysis shows that three trading hubs, even operating over a very large area and market like PJM, are sufficient for hedging most locational risks. A positive aspect of LMP market design is that while numerous energy prices are published, the market can itself select the location and number of hubs useful to mitigate most risks while maximizing liquidity.

Our analysis also raises more questions for future research. First, while our generation dataset includes some battery storage investments, these are too recent and infrequent to allow for detailed econometric analysis. As more battery systems come online, it would be useful to see if LMPs and locational capacity prices affect these investments as well. Second, more research is needed on hedging and market hubs in LMP markets, as these are critical in practice in generation investment.

Third, PJM needs substantial new transmission investment to support both load growth and new (mainly renewables) generation investment. What role, if any, can LMPs play in determining where transmission investment should be prioritized?

Finally, we note that our analysis has analyzed whether LMPs have been significant in determining the location of generation investment. A further analysis could analyze whether the siting decisions made by generators proved advantageous over the long-term on a discounted cash flow basis.

Conflicts of Interest

The authors have no conflicts of interest to declare with respect to this research. Seabron Adamson has advised various clients on issues related to the PJM electricity market but not in the last three years and not on the issues discussed in this paper.

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Annex – Proxy versus generation nodes

As discussed in Section 5, most generation investment is made at locations where there is no existing PJM pricing node. Very frequently, a new pricing node is created by PJM at a new substation or grid connection as the new plant is entering service. For this reason, generation investors must anticipate basis differentials to an existing node to examine historical pricing patterns. Following the logic of a previous paper on ERCOT, we used geographically close existing pricing nodes as a proxy as for LMPs at new generation nodes. However, LMPs reflect marginal congestion (and losses) on the grid, not linear distance. As a result, it is important to evaluate how well the geographically close proxy node method works in practice.

In this brief Annex, we review how well these proxy node LMPs performed in comparison to the actual generation node LMPs over time, as a check on the reasonableness of the geographic proxy methodology used in our analysis.[25]

For each period of length *h* hours the mean error is calculated as:

$$\frac{\sum_{1}^{h}[LMP_{gen} - LMP_{proxy}]/LMP_{gen}}{h}$$

We calculate the mean proxy error over periods of one, three and five years, with each period starting for a given pair of generator and proxy nodes when the generator node comes into service, which is generally when the plant starts commissioning.

Table 8 Mean proxy node error by period

Period	Mean Error
1 year	-0.1%
3 years	-1.0%
5 years	-1.3%

Table 8 shows that the mean errors introduced by use of proxy nodes are relatively modest, which is unsurprising given the number of potential proxy nodes available, which implies that in general new generation locations are close to an existing node (geographically and electrically). The growth in the mean error appears linked to regions where large amounts of new generation enter subsequently (such as SE Virginia and NE North Carolina in the Dominion zone), and which creates some localized transmission constraints for some periods.

25 We use as a sample a set of new plants with capacity greater than 20 MW. PJM does not publish the exact generator node for generators and these must be manually identified using map data . The generator nodes for larger plants can typically be identified by the new node name while for small plants (especially small solar plants) this is often not possible.