How Are Retail Prices Formed in Restructured Electricity Markets?†

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Abstract:
A key challenge in obtaining efficient and competitive retail rates in restructured electricity markets is constructing an appropriate default generation price. Default prices in restructured states are often set by competitive procurement auctions in which firms bid to supply a fixed percentage (i.e., tranches) of a utility's full-requirements load obligation (supply, capacity, ancillary services, and sometimes transmission). Auction clearing prices serve as a price heuristic for other competitive retail supply offers on the open market. Default service also substitutes for competitive retail supply for customers that cannot or will not shop. The efficiency and competitiveness of these auctions, therefore, is of societal importance. In this paper, regression analysis is performed on a unique ten-year dataset of wholesale, retail, and input market parameters for Ohio's four investor-owned utilities to evaluate factors that influence its auction results. The models indicate that auction clearing prices are determined in more complex ways than a simple pass through of wholesale market costs. They indicate that auction competitiveness is a key driver of efficient retail price. They also indicate that wholesale market volatility, which is more challenging for suppliers to hedge, leads to significantly inflated retail auction prices. The paper provides policy implications for the market design of competitive retail electricity markets.

Keywords: Deregulation; Restructuring; Retail Choice; Public Utilities; Electricity Markets; Auctions; Default Supply Service

JEL Classifications: H23; L43; L51; L94

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† **Acknowledgements:** The authors are grateful to the following individuals for their help, comments and research support that shaped or influenced this project: Marcelo Meira, Blain Morin, Kewei Hou, Alberto Lamadrid, Abdollah Shafieezadeh, Yufan Ji, Edward (Ned) Hill, and Gregory Upton. The authors are incredibly grateful for the helpful comments and feedback obtained by participants at the 2022 International Association for Energy Economics meetings and the panel Price Formation in Retail Electricity Markets, and especially to Derek Olmstead, David Brown, and James Conville. The authors also thank Rob Wood and his colleagues at Direct Energy for insightful comments on the paper's conceptual development. The authors also thank the supportive staff at the Alfred P. Sloan Foundation for their support for this research, especially to Evan Michelson and Jessica Klynsma. The authors also thank Casey Crowell and Iliana Varadzhakova at the Intercontinental Exchange (ICE) for their generous data sharing. Any errors, omissions or mistakes in this research are those of the authors and not of any affiliate, organization or funder. Any views or expressions in this work are also solely those of the authors.
Funding: This work was supported by the Alfred P. Sloan Foundation, G-2022-19460.

1. Introduction

The electric power sector underwent significant restructuring in the 1990s and early 2000s that involved the unbundling of several services previously overseen by regulated monopolies. The primary outcome of this unbundling process was the separation of electricity generation from local transmission and distribution, with the latter thought to still exhibit natural monopoly characteristics. These changes were inspired by the deregulation of several other industries, including railways, trucking, and airlines, as well as burgeoning scholarship on the topic of electricity deregulation (Glachant et al., 2021; Hobbs & Oren, 2019; Hunt, 2002; Joskow & Schmalensee, 1983, 1986; Nelson, 2005; Peltzman et al., 1989).

After the uneven implementation of deregulation resulted in several states implementing and then rolling back reforms, fourteen jurisdictions in the US ultimately implemented a form of electricity restructuring that allowed for retail choice.[1] Historically, incumbent local utilities had an obligation (and exclusive franchise) to serve all customers. Retail choice (also knowns as 'retail deregulation,' 'retail restructuring' or 'retail wheeling') introduced the option for third-party suppliers to sell retail generation services. This model was thought to help both wholesale and retail market participants better manage risk (Hogan, 1994; Joskow, 1998). It was also intended to create a market for new electricity products or services and facilitate the pass-through of wholesale costs to retail consumers, potentially with realized savings (Littlechild, 2000; Littlechild, 2002). The states that offer retail electric choice comprise approximately one-third of total retail electric sales in the United States (EIA, 2024b) which is the second largest electricity consumer in the world (EIA, 2024a).[2]

A key market design problem for these states that implemented retail choice, however, was how to establish a "default" service offering, as intended to ensure continuity of retail service to customers who do

[1] Rhode Island, Maine, New Hampshire, Connecticut, Massachusetts, New York, Pennsylvania, Maryland, Delaware, Ohio, Illinois, New Jersey, Texas, and Washington, D.C. The reforms in these states are comparable to those undertaken in parts of Canada, the United Kingdom, Norway, Sweden, Australia, and New Zealand, among other countries (Hoyt et al., 2024).
[2] Other states, such as California, Michigan, and Virginia, offer limited retail choice in specific circumstances. Rules and regulations for retail choice are state-specific and, in many cases, the requirements for municipal, public, or rural cooperative utilities vary.

not (or cannot) choose a third-party provider.[3] All fourteen jurisdictions ultimately adopted a default service construct, and in most cases, the incumbent local transmission and distribution utility absorbed responsibility for the procurement of default service.[4,5] Importantly, default service is fundamentally a substitute for third-party retail supply, and in many jurisdictions default service represents a nontrivial, if not majority, of retail load. Moreover, a growing body of research is demonstrating that third-party retailers use the default service price as a price heuristic, or outright price floor, in setting some or all of their residential contracts (Brown & Eckert, 2018; Dormady et al., 2024; Esplin et al., 2020; Simshauser, 2018; Tsai & Tsai, 2018).

The most fundamental challenge in obtaining efficient and competitive retail electricity rates in restructured electricity markets, therefore, is constructing an appropriate default price. All jurisdictions besides Texas attempted to develop a default pricing mechanism that would reflect the costs of comparable service from third-party suppliers.[6] The theoretical objective of any default pricing mechanism was to create a transitory product that was fair and efficient until the third-party supply market fully developed (Jurewitz, 2002). Designing an efficient pricing mechanism for setting the default price was (and today remains) a challenge. It presents a balancing act, as low default rates can impede customer switching to third-party retailers, and high rates can permit the exercise of market power.

Auction-based procurement was the preferred method for addressing this challenge. Twelve of the fourteen retail choice jurisdictions (all but Texas and New York) eventually adopted competitive, forward

[3] Default service is alternatively referred to as basic, standard, or provider of last resort (POLR) service, depending on the jurisdiction. Additionally, in research, default service contracts are also referred to as regulated retail service contracts. Some customers, such as those on low-income assistance programs with subsidized rates, may be unable to switch suppliers.

[4] In Texas and Maine, retail electric suppliers are responsible for provision of default service. In Texas, the default service product, referred to as POLR service, is administratively assigned to large competitive retail suppliers. POLR prices are deliberately inflated above market cost as a means of inducing adoption of third-party supply. In Maine, the default service product, referred to as the standard offer rate, is competitively procured from third-party retailer suppliers who are selected by the Maine Public Utility Commission.

[5] The incumbent utility, in this case, is indifferent as to whether they provide service to prospective default service customers because associated, profit-making investments (e.g., building generation resources that can earn a regulated rate of return) are, by design, solely competitive market functions.

[6] The degree of comparableness depends on a variety of factors, including the timing of procurement, the costs included (e.g., ancillaries, capacity, transmission, etc.), reconciliation processes, differences in customer acquisition costs, purchase of receivables arrangements, economies of scale, and more. In general, though, both default and third-party service suppliers are wholesale market intermediaries that support full-requirements service to end-consumers. In many cases, the same commercial entities serve both markets.

procurement auctions as their method to develop default supply pricing. Twelve of fourteen jurisdictions (all but Illinois and New York) also implemented full-requirements, load-following contracts for default service, meaning the wholesale supplier offers that clear the auction subsequently absorb all quantity- and price-risk associated with providing default service.[7] The design of these procurement auctions and contracts varies by jurisdiction (Hoyt et al., 2024; Kim, 2013; Littlechild, 2018). Typically, wholesale participants in these auctions bid to serve a fixed percentage (i.e., tranche) of load at a fixed price. Offer prices are expected to incorporate anticipated costs of service, including wholesale energy and capacity, any risk premia, and any competitive margin.

The importance of efficient retail procurement auctions should not be understated. Default rates are crucial to restructured retail market operations in multiple ways. First, due to switching barriers, inertia, lower prices and, increasingly, policy pressure, a high percentage of residential customers continue to receive default supply in all jurisdictions besides Texas (Brennan, 2007; Gamble et al., 2009; Hortaçsu et al., 2017; Ros, 2020; Yang, 2014). Second, as mentioned above, default prices serve as a price heuristic for other competitive retail supply offers on the open market (Brown & Eckert, 2018; Dormady et al., 2024; Esplin et al., 2020; Tsai & Tsai, 2018). Third, procurement of default service creates liquidity in wholesale markets and provides contracting incentives to wholesale generators (Hunt, 2002). Additionally, default service products are reflective of the retail rates obtained by many commercial and industrial customers, who similarly procure full-requirements, load-following service except through bilateral agreement or non-public auctions. For a general discussion, see Brown and Sappington (2023).

Despite the importance of competitive default service products, relatively little research exists exploring how wholesale market conditions influence default service auction results. Moreover, very little research exists relating to auction design, as it does in other auction-based markets (Ausubel et al., 2014; Burtraw et al., 2009; Cramton et al., 2005; Dormady, 2014b; Hortaçsu & Puller, 2008; Krishna, 2009;

[7] New York and Illinois use block-and-index contracts, meaning the default service provider meets its obligations through a mix of pre-purchased "blocks" (i.e., defined energy products transacted in the wholesale market) and ongoing "index" settlement (i.e., spot transactions in the real-time market where quantities in deficit or excess of blocks are purchased and sold, respectively). Under this arrangement, customers are ultimately responsible for true-up costs associated with index transactions on an ongoing basis.

Milgrom, 1989, 2004; Porter & Vragov, 2006). In those other auction-based markets, there exists considerable literature relating to auction structure, conduct, bidding behavior, and input market drivers. This stands in contrast to other equally important topics relating to both regulated and deregulated electricity service and price formation, on which volume upon volume have been contributed. To date, we know very little about how default retail prices are formed, and how wholesale prices, including capacity and derivatives products, influence auction clearing prices. Moreover, very little has been studied regarding market design, including how auction format and structure influences efficiency and competitiveness.

This paper advances these important research questions in several novel ways. We provide the first empirical study of the determinants of retail default price formation in the US. We focus exclusively on retail generation pricing, which is the only component influenced by retail restructuring. We focus on Ohio, which is the largest electricity consuming state within the PJM Interconnection, Inc. (PJM) wholesale electricity market (EIA, 2024b). PJM, in turn, is among the largest competitive electricity markets in the world.[8]

To conduct this analysis, we develop a robust data set consisting of every retail choice auction held in the State of Ohio for over a decade, across all four investor-owned distribution utilities in the State. We develop regression models and incorporate a novel mix of explanatory variables to evaluate the determinants of auction clearing price—both market drivers and auction format and behavior drivers. The data include competitiveness and liquidity features, such as tranche volume, auction rounds and the volume of bidders. The models also evaluate forward settlement prices, load, and capacity. This paper also uniquely accounts for risk by incorporating measures of the implied volatility of forward options. The findings indicate that default auction clearing prices are not simply influenced by wholesale market conditions, but they are also affected by competitiveness characteristics. Specifically, we find that less competitive auctions result in inflated retail prices above the underlying cost of a supplier's full-requirements obligation and that implied volatility and forward market electricity price volatility significantly inflate retail price markups.

[8] PJM is the largest Regional Transmission Organization in the US and serves all or parts of 13 states and Washington, D.C. located in the United States' Mid-Atlantic and Midwest region.

2. Empirical Literature

A great deal of extant research has evaluated efficiency and competitiveness of wholesale (as opposed to retail) electricity markets, across a variety of time periods, regions, and market designs. For a helpful summary of this broad field, see Glachant et al. (2021). Empirical research into price determinants in wholesale markets takes advantage of well-publicized, often highly curated, public pricing data. It is complemented by a much larger body of research evaluating wholesale market design. See e.g., Munoz et al. (2023). However, studies evaluating price determinants in restructured retail markets are few and far between.

Within the broader literature on retail markets, studies generally focus on the question of whether prices have increased over time, or if various policy interventions (e.g., restructuring) have affected retail prices. Recent examples include Bowen et al. (2023), Dormady et al. (2019b), Dormady et al. (2019a), Hartley et al. (2019), and Ros (2017). And for international applications, see Lee et al. (2021), Liu et al. (2019) and Loi and Jindal (2019). A related subset of those studies also focus on efficiency considerations associated with retail restructuring, with an explicit focus on cross subsidies (Amenta et al., 2022; Cicala, 2022; Dormady et al., 2019a; Hartley et al., 2019). This subset generally evaluates the shifting of costs from deregulated market segments (i.e., generation) to regulated market segments (i.e., distribution) following restructuring's mandated divestiture of generation.

Coterminously, there has been a growing body of scholarship relating to pricing efficiencies in retail choice markets. Armed with more disaggregated retail market data, these studies often compare default prices to competitive retail supply offers, or compare those offers to wholesale prices to evaluate markups, or both (Brown & Eckert, 2018; Brown et al., 2020a; Brown et al., 2022b; Brown et al., 2020b; Simeone et al., 2023; Simshauser, 2018; Tsai & Tsai, 2018). Brown et al. (2022b) and Esplin et al. (2020) provide very helpful literature reviews of this important subfield.

This leaves a glaring gap, with essentially no empirical analysis of the functional determinants of those retail prices. In other words, nobody seems to be interested in how those retail prices actually get formed. The default service research that does exist is almost exclusively qualitative in nature. See e.g., Hunt (2002); Littlechild (2003); Tschamler (2006). This we suspect is driven heavily by data limitations in state- and utility-level retail data. For example, Littlechild (2018) reviews the methods used to regulate and set default rates and discusses the impacts that default regulation has on market competition (supplier pricing, supplier entry/exit, customer switching, etc.). To develop this overview, Littlechild conducted interviews with key stakeholders, reviewed regulatory filings, and evaluated existing literature related to retail choice markets. This and other evaluations do not empirically assess how variation of procurement design, auction participation, market conditions, or other factors can influence procurement outcomes.

The exception to this is the advancement provided by Brown et al. (2022a), in a study of default service auctions in Alberta, Canada. They develop a mean-variance utility function to evaluate the performance of load-following default service auctions in Alberta from December 2018 through April 2021. They find that default service prices exceed the expected risk premium of a counterfactual break-even pricing model, but by amounts that decrease over time. They also find prices fall as the level of competition (i.e., number of bidders) increases and that bids incorporate both price (i.e., spot price variance) and quantity (i.e., load obligation) risk.

While many of the core theoretical findings from Brown et al. (2022a) are applicable, there are some key contextual and market design differences that limit the applicability of their findings to US retail markets. First, Alberta's wholesale market is relatively small and therefore more sensitive to factors like expected generation outage rates and oil prices (which influence electricity demand in the region). Alberta also lacks a capacity market, as applicable in all U.S. retail choice jurisdictions besides Texas. Second, Alberta's default service procurement approach is distinct from the approach used in most U.S. markets. For example, Alberta features short-term procurements (one month), whereas in most US jurisdictions, procurements can extend to 36 months, or longer. In Alberta, this results in frequently changing prices. Additionally, Alberta's full-load auctions are for energy products only, not full-requirements as in most U.S. markets, and are procured less far in advance. As a consequence, these auctions do not reflect the same liquidity challenges and risk variation inherent to longer duration contracts. Finally, their study focuses on a nascent policy intervention and, as a result, the data set reflects less variation. It also uses oil and gas futures and previous 30-day spot prices to measure factors like forward price expectations and volatility, rather than power futures and the value of derivatives, which are more commonly utilized by active traders.

3. Essential Background on Auction Format and Structure

Auction format and structural characteristics can play a critical role in influencing bidding behavior and price formation, which is well established in the auction theory literature. See e.g., Dormady (2013); Dormady (2014b); Hortaçsu and Puller (2008); Krishna (2009); Milgrom (2004); Weber (2004). Across all distribution utilities and over the duration of our study, auction format itself is generally unchanged and consistent, with some caveats noted below. This consistency is due to the fact that Ohio statute requires the use of auctions and sets forth the general auction structure, known as the competitive bidding price (CBP) process.[9] Because of the importance of auction structure to price formation, we describe specific structural characteristics and auction clearing rules used in SSO procurement auctions.

Auction managers retained by each of the four distribution utilities in Ohio each proposed an initial auction format that the PUCO subsequently adopted and has since implemented with consistency. See Roach et al. (2012). Each SSO procurement uses a descending clock auction format with a possible final sealed-bid round to clear inframarginal demand (i.e., ensure tranche volume matches the load obligation). Each distribution utility's auctions require winning bidders to provide full-requirements service for the forward contracted procurement period. "Full requirements" includes energy, capacity, market-based

[9] Ohio Revised Code (ORC) 4928.142, 4928.143 and 4928.543 require that default electricity prices for the standard service offer (SSO) be set by competitive bidding price (CBP) auctions. The format and technical details for the structure of each auction is delegated by statute to the Ohio Department of Administrative Services, the administrative agency responsible for State procurement. Appropriately, that agency further delegates the responsibility to the Public Utilities Commission of Ohio (PUCO), who integrates its auction responsibilities into the retail rate-setting tariff mechanism known as the Electric Security Plan or ESP (see Dormady et al., 2019 for a detailed regulatory history) of each distribution utility. Pursuant to that retail rate-setting process, each distribution utility retains a third-party auction manager as a consultant with experience managing and operating procurement auctions. AEP Ohio retains NERA Economic Consulting, and the other distribution utilities all retain Charles Rivers Associates. These two consultants each choose to use the same auction format and price clearing rules throughout each service territory in Ohio. The PUCO adopts these consultants' auction designs and rules through each utility's ESP. For original CBP case dockets see: Case No. 12-3254-EL-UNC (AEP Ohio); Case No. 10-2586-EL-SSO (Duke); Case No. 12-0426-EL-SSO (DPL); Case No. 10-388-EL-SSO and 09-0906-EL-SSO (FirstEnergy).

transmission service and market-based ancillary services.[10] This approach is generally consistent across the duration of our study with several minor caveats.[11]

Product quantity is separated into tranches, each representing 1% of net SSO load for a given utility, irrespective of customer class (e.g., residential, commercial, industrial). A bidder winning a single tranche obtains an obligation to service all full requirements needs for 1% of that utility's SSO load for the duration of that forward maturity. Notably, competitive retail electric service (CRES) customer load is excluded from SSO auction procurement as CRES marketers provide their own generation, capacity, and other market-based services. For example, a hypothetical bidder winning 17 tranches in AEP's March 6, 2018 auction has an obligation to provide 17% of the generation and capacity required to service AEP Ohio's SSO customers between the delivery dates of 6/1/2018 and 5/31/2020 (i.e., over a 24-month maturity). The extent of retail choice activity, or customer "switching," can indicate market activity.

The design of SSO auctions creates circumstance where the actual cost of servicing load presents bidders with load uncertainty related both to the amount of energy required during particular on- and off-peak hours and also peak load contribution (PLC) used to assign capacity costs. This uncertainty is in addition to price uncertainty regarding the costs of full requirements. These uncertainties are addressed by winning bidders through their bids as they incorporate risk premia or the costs of hedging instruments that reflect risk preferences. Additionally, because retail choice activity occurs conterminously, the volume of load is also subject to uncertainty because the number of customers who will switch away from default service is subject to variation.

[10] Network Integration Transmission Service (NITS), firm transmission and transmission scheduling, system control and dispatch, as well as reactive supply and voltage control, among other non-market costs, remain the responsibility of the distribution utility. Limited exceptions to this approach apply for certain large customers receiving third-party supply and on a pilot basis (e.g., see PUCO (March 31, 2016). *Opinion and Order*. Case No. 14-1297-EL-SSO).

[11] Ohio's regulatory history and its electric security plan (ESP) process modified some of the auction rules and supplier obligations over time, which we note here and account for in our data and analysis. First, one of the four distribution utilities, AEP Ohio, did not require SSO suppliers to provide capacity, transmission, or ancillary services prior to its third ESP (i.e., prior to 2015). Its first four auctions were energy-only contracts, and not full-requirements obligations (see Case No. 12-3254-EL-UNC). Second, another distribution utility, FirstEnergy Ohio, included NITs, transmission, ancillary service, and other related costs in its full-requirements obligations prior to June 1, 2011, at which time FirstEnergy Ohio was integrated into the PJM Interconnection, LLC (PJM) market (see Case Nos. 09-906-EL-SSO and 10-388-EL-SSO).

Some elements of auctions vary by design or circumstance over the course of PUCO auction history. For example, the duration, or maturity, of the forward delivery contract is usually either 12-, 24-, or 36-months. Likewise, forward delivery contracts have generally ended on the 31st of May, meaning that consumers have historically observed seasonal retail price changes beginning the 1st of June.[12] Other elements that vary include the time between procurement and product maturity, procurement month, and bid reference prices. We exploit this heterogeneity in our analysis, as discussed below.

We note that contract maturity in Ohio is longer than other default service procurement contracts utilized in other jurisdictions such as Alberta Canada (Brown & Eckert, 2018) and northeast states in the Independent System Operator - New England (ISO-NE) market (i.e., New Hampshire, Maine, Massachusetts, Rhode Island, and Connecticut). It is, however, generally consistent with procurement contracts used in other PJM Interconnection, LLC (PJM) jurisdictions with retail choice (i.e., District of Columbia, New Jersey, Delaware, Maryland, and Pennsylvania) (Hoyt et al., 2024). A handful of early auctions (ten auctions in total across all utilities) were for forwards of a different length to facilitate price blending in the transition away from regulated generation prices, and these forward durations are specifically incorporated into our empirical data. And while maturity is generally consistent at one of the three above forward durations, the lead time between the date at which the auction is held and the initial delivery period thereafter is heterogeneous. The amount of lead time ranges from as few as 18 days prior to the first day of delivery, to as great as 376 days out, with an average lead of 128 days between the date at which the auction is held and the initial starting date of product delivery.

The choice of auctions to supply default service, as well as many of the auction features and design elements adopted by Ohio, reflects the recommendations offered in the academic literature at the time Ohio implemented retail restructuring and constituted SSO products. For example, Jurewitz (2002) describes a model approach where the local distribution utility "remains the default service retailer but solicits competitive bids from wholesale suppliers willing to supply full-requirements power for a fixed period

[12] June 1 coincides with the beginning of PJM's delivery year, which runs from June 1 through May 31.

(e.g., one year) to groups of customers" (p.82). In this way, Ohio's approach can be understood as representing model design features even as some specific characteristics varied by utility or over time. Further details regarding the auction format structure and bidding process are provided in Appendix A.

4. Data

We draw upon several unique data sources for empirical analysis. The overarching rationale for variable selection and analysis is the identification of factors that influence bidder behavior and competition in the auctions. During variable selection, we also consulted with active electricity commodity traders. For ease of exposition, we categorize variables into one of two categories: 1) wholesale input market variables, and 2) auction structure and performance variables. The first includes wholesale market characteristics necessary for evaluating the costs of servicing SSO retail load from wholesale markets, including costs associated with acquiring and/or hedging full-requirements services for winning tranche obligation bids. Second, this includes characteristics associated with the auction itself in terms of structure, composition, and competitiveness that are publicly available or can be derived from available information.

The unit of analysis is the individual procurement auction, and the main dependent variable is the final net auction clearing price. While some variables are available at the hourly level (e.g., hourly historical SSO load), these inputs are aggregated up or temporally adjusted (e.g., load-weighting price variables) to evaluate specific predictive characteristics applicable to auction clearing price and SSO price formation. It is also common practice to hold multiple auctions on the same day, but for different forward delivery periods, or maturities. Auctions held simultaneously for two or more different delivery periods are treated as separate auctions (i.e., each individual auction is a unique data point), as they appear to bidders.[13] The analysis data set includes 24 unique instances of multiple auctions held on the same date but for different forward positions or maturities. For example, on April 11, 2017, Dayton Power and Light held three

[13] Readers familiar with emissions permit auctions of multiple unique vintages on the same auction date should be familiar with the need for this distinction. See, e.g., Armantier et al. (2013); Dormady (2013, 2014a); Dormady and Healy (2019).

auctions on the same day: one 12-month forward product at a volume of 16 tranches, one 24-month forward product at a volume of 17 tranches, and one 36-month forward, also at 17 tranches.

The time period for the dataset spans from the earliest procurement auctions held by FirstEnergy on October 20, 2010 to the latest auctions held in 2022. Other utilities began their procurement auctions between 2011 and 2014, depending upon the authorization of their initial ESP by the PUCO. Auctions held later than 2022 are not included in the dataset due to the absence of realized load and other key variables not available during the forward procurement window, including the switching rate. In total, the dataset consists of 120 auctions across four utilities, inclusive of 31 auctions for AEP, 29 for Duke, 19 for DP&L, and 41 for FirstEnergy.

4.1 Wholesale Market Variables

Wholesale market variables are incorporated for the purpose of evaluating bidder cost expectations. These include characteristics of current or future (i.e., expected) wholesale costs for delivered energy or capacity. Note that, in Ohio, wholesale transmission costs are assessed to electric distribution utilities outside of the SSO procurement process and, therefore, appropriately excluded from the wholesale market variables. FERC jurisdictional transmission costs (e.g., PJM Network Integration Transmission costs) are treated similarly to other distribution costs for purposes of customer billing Wholesale data elements can be conceptualized as information that the bidders would use to construct their bids at the time of the auction. This informs how bidders identify the costs that they will incur in providing full-requirements service to meet their obligations for any tranches they win at the auction.

Each of the four regional electric distribution utilities in Ohio participate in the PJM Interconnection.[14] Consequently, the most relevant electricity market details are specific to the PJM regional wholesale marketplace. For wholesale energy price variables, we collect PJM on-peak and off-peak monthly forward electricity prices at PJM Western Hub (West Hub) over the duration of each

[14] PJM Interconnection LLC (PJM) is the largest Regional Transmission Organization (RTO) in the US and serves all or parts of 13 states and Washington, D.C. located in the United States' Mid-Atlantic and Midwest region.

contract's maturity. West Hub is among the most liquid trading hubs in PJM and is proximate to energy delivery points in Ohio. As a result of its proximity and liquidity, West Hub forward pricing is a common index for Ohio wholesale electricity, with differences between West Hub prices and actual LMP referred to as 'basis.' Basis reflects the costs of congestion and losses, and can be negative or positive. We used S&P Capital IQ Pro, a subscription market research tool, to access West Hub data from the NYMEX commodity futures exchange.[15] More specifically, for each auction date, we create a time series (not to be confused with our auction unit data which are cross sectional) of the monthly on-peak and off-peak clearing price for the forward delivery period associated with each auction, as they existed historically on the day on which the auction was held. We employ the PJM definition of on-peak hours, which are non-holiday, weekday, delivery hours between 07:00 and 22:00. Remaining hours are defined as off-peak.

For example, if a utility held an SSO auction for a 12-month delivery period on April 1, 2015 for a maturity period of June 1, 2015 to May 31, 2016, then we create two time series of the forward prices (i.e., the on-peak and off-peak forwards) for each month between June 2015 and May 2016 as they were known as of the date of the auction. That is, forwards established on the auction date of April 1, 2015. This approach is useful because both on-peak and off-peak forwards, as separately formed in exchange markets, represent a point-in-time assessment of expected market prices based on conditions at the time the bids were placed into the SSO procurement auctions. On- and off-peak forward contracts are also used by bidders to hedge price risk.

Implied volatility for PJM West Hub is also evaluated. This represents the expected variability implied by the underlying options markets and provides some insight into the underlying cost of suppliers to hedge their load obligations. We obtain historical PJM West Hub calls and puts on the Intercontinental Exchange (ICE), and we apply Black (1976) to calls to calculate implied volatility. This implied volatility can be interpreted as a measure of how much risk a bidder might be exposing itself to due to volatility of the underlying commodity price.

[15] NYMEX is a commodity futures exchange owned by CME Group.

We collect hourly load data from the CBP auction websites for each distribution utility. We classify load by PJM on-peak or off-peak period and then aggregate to the month. From these aggregated monthly loads, we sum the on-peak and off-peak loads for each auction contract. The use of actual historical load data assumes perfect foresight into load requirements. We prefer this approach to the historic forecasting approach used by Brown et al. (2022a) because of the longer forecasting horizons required for maturities in this context, and because each bidder's own internal load forecasts are unobservable.

In addition to the load itself as an attribute of the auction, we also use the monthly on- and off-peak load data to derive load-adjusted energy and capacity price variables. Using the same example as above, for the 12-month contract with delivery periods between June 2014 and May 2015, we multiply the forward price of each procurement month from PJM by the actual load provided by a given distribution utility in that procurement month, sum the resultant variable, and then divide by the total load over the 12 months. We do this both for on-peak and off-peak loads, and we create a single metric that weights the forward prices by the total load (i.e., on-peak + off-peak load). The resultant variables are total, on-peak, or off-peak load-weighted forward prices (i.e., average prices after adjusting to account for the actual amount of load in each forward period). We use a similar load-weighting process to load-adjust the capacity cost to isolate relevant costs for each auction, as described below. Using load-weighting allows us to capture in a single variable the energy and capacity cost that would be incurred by tranche winners.

We also control for capacity cost. Instead of using the simple base residual auction (BRA) price from PJM, capacity prices are more accurately derived using the Final Zonal Net Load Price ($/MW-day), which represents actual capacity costs after accounting for both the base and follow-up residual auctions for each locational deliverability area (i.e., capacity zone). These costs are subsequently converted into $/MWh figures in order to represent capacity in the same terms as the auction bid prices. The full cost of capacity equals the Final Zonal Net Load Price multiplied by each service territory's adjusted capacity peak load contribution (PLC) for all customers. The PLC represents the unforced capacity obligation of all customers in the service territory multiplied by a zonal scaling factor and a forecast pool requirement scaling factor, both of which ensure adequate recovery of capacity costs. The full cost (in dollar terms) can then be divided by usage during the full delivery year to calculate a per unit rate. This rate is subdivided into proportional SSO and CRES capacity costs based on their relative contribution to PLC. This relative contribution is identified on a daily basis in the load data presented on the CBP auction website. We derive SSO customer's per-kWh capacity costs for each auction period based on the applicable forward months and using materialized, actual SSO load, i.e., assuming perfect foresight into capacity costs. For a few auctions at the end of the study period, forecast capacity prices and load are used in place of actual load to address partial data coverage.[16]

We also utilize a separate set of natural gas variables as wholesale market inputs. These include both current and forward gas prices, as well as the implied volatility of gas. We draw upon daily Henry Hub prices as of the date of the auction for models using the current gas price, and we use historical S&P Capital IQ data for forward gas prices as of the historical date of the auction for models using the forward gas price. The former evaluates the impact associated with current prices, while the latter evaluates the impact of future gas price expectations over the forward procurement horizon as it was known on the morning the auctions were held. We collect a historical daily timeseries of the 30-day implied volatility of natural gas futures from Bloomberg terminal. We use the 30-day ATM (at the money) implied volatility at 100% moneyness. This timeseries reflects the anticipated future volatility of a security's price and we evaluate it as a potential determinant of the auction's clearing price.

Because of the close interplay natural gas price and wholesale electricity price (Dormady et al., 2019a), as gas is generally the marginal fuel input on the day-ahead market in PJM, we separate gas and wholesale electricity variables and estimation models. Wholesale market variables are summarized in Table 1.

[16] Forecast load for unrealized months as of the time of this analysis was set equal to actual monthly load during the most recent preceding equivalent month where there were known load figures (e.g., January 2024 data represented using January 2023 load). For FirstEnergy and AEP, forecast loads were also adjusted for anticipated aggregation activity. Projected aggregation related migration for FirstEnergy was provided by their auction manager. Projected aggregation-related migration for AEP was developed based on the average level of migration attributable to aggregation according to data provided by the auction manager applied on a going forward basis. Forecast capacity was based on S&P Capital IQ Plus's projected PJM RTO area capacity prices for DY 24/25 and DY 25/26.

Table 1. Wholesale Market Variables Summary

Variable	Summary	Source	Temporal Granularity
Forward On-Peak Mean Price	Mean forward prices on the date of the auction for the respective delivery period for on-peak hours.	S&P Capital IQ	Daily
Load Weighted Forward On-Peak Mean Price	Mean forward prices on the date of the auction for the respective delivery period for on-peak hours, weighted by load for the respective on-peak hours.	S&P Capital IQ, Derived by Authors	Daily
Forward Off-Peak Mean Price	Mean forward prices on the date of the auction for the respective delivery period for off-peak hours.	S&P Capital IQ	Daily
Load Weighted Forward Off-Peak Mean Price	Mean forward prices on the date of the auction for the respective delivery period for off-peak hours, weighted by load for the respective off-peak hours.	S&P Capital IQ, Derived by Authors	Daily
Total On- and Off-Peak Load-Weighted Mean Forward Price	The total around-the-clock forward price weighted by hourly load (based on hourly loads and daily forwards) for all hours in the forward delivery period.	S&P Capital IQ, Derived by Authors	Daily
On-Peak Load	Total load for on-peak hours (in MWh) for the SSO tranche obligation and delivery period being auctioned (actual realized load).	CBP auction managers for each distribution utility	Hourly
Off-Peak Load	Total load for off-peak hours (in MWh) for the SSO tranche obligation and delivery period being auctioned (actual realized load).	CBP auction managers for each distribution utility	Hourly
Load Weighted Capacity Cost	Final Zonal Net Load Price multiplied by each service territory's adjusted capacity peak load contribution (PLC) for SSO.	CBP auction managers for each distribution utility; PJM; Derived by Authors	Daily
PJM West Hub Implied Volatility	The implied volatility of options trades in PJM West Hub	Intercontinental Exchange (ICE), Derived by Authors	Daily
NYMEX Henry Hub Price	The NYMEX Henry Hub price the day of the auction in MMBtu.	S&P Capital IQ	Daily
NYMEX Implied Volatility	The 30-day ATM implied volatility OF NYMEX on the date of the auction	Bloomberg Terminal	Hourly
Forward NYMEX Price Mean	Mean natural gas forward price in MMBtu calculated as the average across all forward months in the delivery period on the date of the auction	S&P Capital IQ, Derived by Authors	Monthly

4.2 Auction Structure Variables

The second category of variables relates to auction structure. They are incorporated for the purpose of evaluating the characteristics of each procurement process that influence prices. The source of all auction variables is the CBP auction managers websites for each distribution utility. Each website lists the dollars per megawatt-hour price at which each auction cleared, which is the main dependent variable in the empirical analysis. The auction clearing price represents net tranche price, meaning the price net of all individual winning bids (and not necessarily the price of any individual winning bidder). It is this price that is used in the price blending process described in Appendix A.

Other auction structure variables identified from the CBP auction websites include: the length of the delivery period, also called the forward length or the maturity, represented as days and months; the target tranche size and the amount of tranches sold; details pertaining to the bid prices of the starting round of the auction, which may indicate the initial competitiveness or price expectations of bidders; count of registered bidders; count of winning bidders; and the count of rounds in the auction. Several of these variables were evaluated for their potential indication of competitiveness, as described below. The auction variables are summarized in Table 2.

Table 2. Auction Variables Summary

Variable	Summary
Price	The net clearing price of the SSO procurement auction
Registered Bidders	Count of bidders registered for the auction
Winning Bidders	Count of winning bidders who received tranche obligations
Tranches for Sale	The percentage of the utility's SSO load obligation to be procured
Tranches Sold	The percentage of the utility's load obligation that was sold/procured
Delivery Period	Start and end dates of the forward period of procurement contracted at auction
Forward Months	Count of the number of months of the forward commitment to supply SSO (between the beginning and end delivery date) and NOT counting the lag between the date of the auction and the beginning of the delivery period
Auction Rounds	Count of rounds in the auction
Starting Bid Price Minimum	Minimum price of starting bids in first bidding round
Starting Bid Price Maximum	Maximum price of starting bids in first bidding round

Note: All listed variables are sourced from the CBP auction websites for each distribution utility and auction ID.

4.3 Descriptive Statistics

Table 3 provides descriptive statistics for the variables utilized in the econometric analysis. The auction clearing price, which is the main dependent variable, ranges from a minimum of about \$36/MWh to a maximum of \$122.50/MWh. The mean of the series across all four utilities is \$54/MWh (i.e., 5.41 cents/kWh). Retail SSO customers pay corresponding rates after accounting for non-bypassable generation riders (Dormady et al., 2019b).

The total, all-hours load-weighted wholesale forward electricity price has a mean value of \$38/MWh, and ranges from \$27/MWh to \$101/MWh. The simple mean difference between procurement auction price and the total load-weighted wholesale forward price is \$15.67/MWh. This difference represents the retail markup, before accounting for additional explanatory controls.[17] The wholesale

[17] The simple markup between the total all-hours load-weighted wholesale forward price and the retail auction clearing price is statistically larger for the three utilities with auction management by Charles Rivers Associates. AEP, which is the only utility with auctions managed by NERA Consulting, has a historical average of approximately 2.2 more bidders per auction (Wilcoxon $p<0.000$). As such, it has historically had a 22.2 percent lower simple average markup compared to the other three distribution utilities (Wilcoxon $p<0.037$).

forward prices for on-peak and off-peak hours had means of $44/MWh and $32/MWh, respectively.

On-peak and off-peak load also have similar descriptive statistics and differ on the maximum end. The values are reported in millions of MWh, and we log the values for econometric estimation. Total load increases with maturity length, as longer delivery horizons correspond to higher procurement volumes. Capacity costs, which we also weight by hourly load as described above, range from zero to $25.82/MWh, with a mean of $10.59/MWh.

The current Henry Hub price for natural gas as of the date of each auction has a mean of $3.28/MMBtu, and ranges from about 1 dollar to about 7 dollars. Similar descriptive statistics are observed for the forward Henry Hub price. Comparing the two, we observe slightly larger mean values and moderately lower standard deviations for the forward gas prices. Mean value differences are not statistically different ($p<0.339$). However, we perform a Variance-Ratio test using Armitage et al. (2002) and find that the forward gas prices have statistically lower standard deviations by about 28 percent ($p<0.007$), indicating that forward positions on gas exhibit moderately less volatility.

The two implied volatility measures for NYMEX (natural gas) and PJM West Hub (electricity) have mean values of 45.8 and 31.4, respectively.[18] The former ranges from 21.2 to just over 108, and the latter ranges from 15.9 to just under 86. The medians of these two variables are 42.4 and 24.3, respectively. Implied volatility measures are also referred to colloquially by traders as an indicator of market fear, and the authors learned from one professional trader that implied volatilities for PJM West Hub above 50 (which is almost exactly the 90th percentile in our dataset) are treated as particularly risky, and values greater than 80 (which are in the top one half of one percent in our data) send cautionary market exit signals to bidders.

The count of registered bidders ranges from 5 to 15, with a mean value of about ten bidders. The volume of tranches ranges from 0.1 to 1.0, which is the difference between auctioning ten percent of the SSO load obligation to the full load obligation in a single auction. The latter represents an 'all eggs in one basket' approach to procurement. On average, auctions in Ohio obtain a little more than 22 percent of the

[18] Implied volatility values for the years 2011 through 2013 were not available from ICE markets, and some estimation models relying on those values omit those early years.

total SSO obligation. The forward duration, or maturity, ranges from 5 months to 41 months. Most auctions, however, are 12-, 24- or 36-month forward commitments. See table A1 in Appendix B for auction variable summary statistics by distribution utility.

Table 3. Summary Statistics

Variable (and unit)	Mean	St. Dev.	Min.	Max.
Price (SSO Auction Clearing Price) ($/MWh)	54.139	15.726	36.740	122.500
Total On- and Off-Peak Load-Weighted Mean Forward Price ($/MWh)	38.469	10.692	27.014	101.753
Forward On-Peak Mean Price ($/MWh)	43.977	12.133	30.373	113.280
Load Weighted Forward On-Peak Mean Price ($/MWh)	44.356	12.255	30.757	113.214
Forward Off-Peak Mean Price ($/MWh)	31.891	8.877	22.524	82.390
Load Weighted Forward Off-Peak Mean Price ($/MWh)	32.429	9.264	23.110	89.833
On-Peak Load (Millions MWh)	6.536	3.812	1.897	18.157
Off-Peak Load (Millions MWh)	6.353	3.715	1.822	17.713
Load Weighted Capacity Cost ($/MWh)	10.596	4.714	0.000	25.824
NYMEX Henry Hub Price ($/MMBtu)	3.281	1.179	1.653	7.820
Forward NYMEX Price Mean ($/MMBtu)	3.412	0.918	2.225	7.479
NYMEX Implied Volatility (Index)	45.853	18.419	21.210	108.460
PJM West Hub Implied Volatility (Index)	31.356	13.971	15.955	85.979
Registered Bidders (Count)	10.775	2.243	5.000	15.000
Tranches for Sale (Percent of load)	0.225	0.124	0.100	1.000
Forward Delivery Duration (Months)	20.425	9.628	5.000	41.000

5. Econometric Approach

It is well established that employing multiple statistical control factors in a regression model and estimating it via Ordinary Least Squares (OLS) may fail to produce reliable estimates of causal effects in the presence of confounding effects. This is particularly the case when the empirical model imperfectly captures omitted terms that are related to both the dependent and independent variables, or more specifically, where the error term is related to the assignment of the treatment and hence the outcome. One way in which this can be addressed is by using an Instrumental Variables (IV) method that helps to remedy this issue and establish causality under certain conditions (Angrist & Pischke, 2008; Morgan & Winship, 2014; Wooldridge, 2010). This estimation approach is well-suited to the contextual features of our data and the framework of study.

The rationale for this approach is supported for the evaluation of the final net auction clearing price as the main dependent variable in a structure in which the unit of analysis is the individual procurement auction. Auction theory suggests that auction competitiveness is an essential driver explaining auction clearing price (Krishna, 2009; Milgrom, 2004; Weber & Milgrom, 2000). We operationalize competitiveness as the count of losing bidders in an auction, given by the difference between registered bidders and winning bidders. However, by selecting an IV approach, we are implicitly assuming that competition is endogenously linked to price in the context of wholesale electricity markets. This implies that random or specific shocks not accounted for in the models simultaneously affect auction clearing price and the count of registered or losing bidders. Thus, endogeneity can lead to biased and inconsistent parameter estimates challenging causal inference.

However, the IV method leverages the naturally occurring data and allows for valid estimations if two conditions are met: relevance and exogeneity. The first condition suggests that the instrument must be a good predictor of the count of losing bidders and is often considered empirically satisfied if the F-Statistic of the first stage regression is greater than 10 (Stock et al., 2002). The second condition suggests that the instrument must be independent of the error term in the main regression, ensuring that the instrument does not directly affect the auction clearing price, except through its influence on the count of losing bidders (Angrist & Pischke, 2008; Wooldridge, 2010).

The instrument utilized in the present research is the switching rate (i.e., share of customers that have "switched" away from SSO service and adopted competitive supply) at time *t,* as of the date of auction *a* for distribution utility *d.* Switching rate is reported by the PUCO both as the percentage of each tariff class's total consumption in MWh and based on the raw count of customers.[19] Here, we utilized the former, the total switch rate as a function of net distribution utility consumption, summed across all tariff classes.

There is a strong theoretical justification for the use of switching rate as an appropriate instrument for registered bidders, or losing bidders, which in turn provides a strong proxy for auction competition. Switching rate can only affect the auction clearing price through these competition variables. The auction clearing price, which is reflected in dollars per megawatt hour, reflects the marginal cost of servicing generation and capacity, for which price determination is conditioned upon a larger 13-state wholesale market and not influenced by the retail choice activity of any single utility or within any member state.

[19] The PUCO reports electric customer choice activity pursuant to ORC 4935.01 and OAC 4901:5. Activity rates can be found at: https://puco.ohio.gov/utilities/electricity/resources/ohio-customer-choice-activity

Wholesale energy or capacity prices in the larger market have no relationship to a utility's retail switching rate since wholesale prices are reflective of the costs to serve *all* customers, switched or unswitched.[20]

There is also a strong empirical justification. Postestimation endogeneity tests performed on the empirical models developed by Durbin (1954), Wu (1974) and Hausman (1978) can identify if the regressors are in fact endogenous. Here, we utilize the Wooldridge (1995) modified version of this test for robust standard errors on each regression model and find that the test supports the statistical significance of the instrument. This is the case at $p<0.10$ in all models, except the two forward gas models (models 8 and 9) which are significant at $p<0.17$.

However, switching rate can influence how many bidders register for and compete in the SSO auctions. Switching rate sends a signal to potential auction registrants at the registration phase (see Appendix A for details of SSO auction pre-registration process) about the worthwhileness of auction participation. It does so by reflecting both the extent of potential customer inertia and the prospective bidder's potential market exposure. Inertia in retail choice markets is the subject of an extensive body of literature (Brennan, 2007; Gamble et al., 2009; Giulietti et al., 2005; Hortaçsu et al., 2017; Yang, 2014). A lower switch rate signals higher customer flight potential in a growing market. It also signals a declining prospective margin after accounting for the fixed costs of participation (e.g., preparing registration materials, assessing market conditions, committing resources to the auction process, credit qualification). Further, switching rate reflects market exposure, particularly among bidders with generation assets seeking to utilize the SSO auctions as a stable and profitable generation hedge. Expected instability in the switching rate (e.g., more headroom to increase) can signal challenges obtaining a stable hedge and therefore discourage auction participation.

Formally, we aim to identify the effect of a change in competition as operationalized by the count of losing bidders through a series of two-stage least squares regression models (2SLS). In the first stage,

[20] Of note, switching rate and load (either for on-peak hours, off-peak hours, or in the aggregate) are uncorrelated with one another. During instrument selection, the authors also ran reduced-form bivariate regression models (not presented here) with the instrument predicting load, including utility and year fixed effects, and the instrument's coefficient was not statistically different from zero. This provides strong justification that the instrument does not impact price through load, and that the instrument is independent.

we regress the number of losing bidders $y_{a,d}$, who participated at auction *a* of distribution utility *d*, on the exogenously-determined switch rate $\zeta_{t,d}$ reported for auction date *t* of distribution utility *d*, with a vector of exogenous variables that are also included in stage two. This process is needed to obtain a consistent estimator and to provide information on y (i.e., the instrumented variable). Following stage one, in stage two, we regress the outcome of interest, $p_{a,d}$, namely the net clearing price of auction *a* performed by distribution utility *d* on previously estimated values of losing bidders $y_{a,d}$.

In an effort to be consistent, we present below a general structure of *i* instrumental variable models (where *i* ranges from 1 to 9 [see estimation results in next section]). We assume the scalar dependent variable for each structural model *i* is represented as $p_{a,d}$, which depends on one endogenous regressor denoted by $y_{a,d}$ and K_i exogenous regressors (including intercept). These exogenous variables are important considerations for wholesale market energy traders and include: tranches for sale during the auction, load-weighted capacity price, and implied volatility of natural gas. Each structural model *i* also incorporates specific exogenous variables as described in the previous section. For each model, we separate the vector of exogenous regressors into auction variables x_c, and market variables x_m.

Following the structural (i.e., stage-two) model, we present the first stage equation, which also contains the set exogenous variables x_c and x_m, and the instrumental variable $\zeta_{t,d}$ (i.e., switch rate) on the right-hand side. Both sets of equations are presented below. The coefficient of interest is $\gamma_{1,i}$, which should give us unbiased estimate of the relationship between number of losing bidders and auction clearing price for each of the *i* empirical models that follow.

Structural Model: $$p_{a,d} = y_{a,d}\gamma_{1,i} + \boldsymbol{x_{a,d,m,i}}'\boldsymbol{\beta_{m,i}} + \boldsymbol{x_{a,d,c}}'\boldsymbol{\beta_{c,i}} + \boldsymbol{\theta_d}'\boldsymbol{\beta_{d,i}} + \boldsymbol{\tau_T}'\boldsymbol{\beta_{T,i}} + u_{a,d,i} \qquad (1)$$

First stage: $$y_{a,d} = \zeta_{t,d}\delta_{1,i} + \boldsymbol{x_{a,d,m,i}}'\boldsymbol{\rho_{m,i}} + \boldsymbol{x_{a,d,c}}'\boldsymbol{\rho_{c,i}} + \boldsymbol{\theta_d}'\boldsymbol{\rho_{d,i}} + \boldsymbol{\tau_T}'\boldsymbol{\rho_{T,i}} + v_{a,d,i} \qquad (2)$$

As can be seen in equations 1 and 2, we are not assuming auction clearing prices to be correlated by utility *d* or by year *T* (i.e., we are not grouping observations into clusters). However, we have included utility θ and year τ fixed effects to control for any idiosyncratic or secular variation, respectively. There is also a strong theoretical justification for not utilizing a model with clustered observations. The clustering assumption assumes that exogenous shocks are independent between clusters (i.e., between utilities). However, that is not operationally the case. The four distribution utilities in this study all operate in the same PJM wholesale market and are subject to the same exogenous shocks in input costs for energy, capacity, and ancillary services. It would be logically inconsistent to suggest that a shock to input fuel costs would hit one utility's procurement costs differently from the others. They are also each regulated by the same regulator, the PUCO. Additionally, each auction generally includes the same or similar set of suppliers as bidders, though that is not publicly observable. From an econometric perspective, there are also important reasons for not estimating this model with clustered observations. As indicated by Cameron and Miller (2015), clustering relies upon the assumption of a large number of clusters, which is impractical in this study because there would only be 4 clusters (utilities).

6. Empirical Results

Regression results are presented in Tables 4 and 5. Consistent with Dormady et al. (2019a) models based on the wholesale price of electricity (PJM West Hub) as an input predictor are separated from models based on the natural gas price (NYMEX) because of the close interplay between the two markets given that natural gas is generally the marginal wholesale input fuel in PJM. Models separately include on-peak and off-peak load over the duration of the forward delivery contract being auctioned, in both cases in log form.

The wholesale electricity models (Models 1-5) separately estimate the effect of forward prices for on-peak versus off-peak hours in the forward delivery period being auctioned. They also separately estimate these forwards adjusted by hourly load and include on- or off-peak load as separate variables. These variations are used to effectively evaluate the marginal contribution of each variable. Model 1 includes the aggregate total on- and off-peak load-weighted West Hub price forward. The gas models (Models 6-9) are broken down into two sets of models: those based on the NYMEX price as of the day of the auction, and those based on the forward NYMEX price for the forward delivery period as of the day of the auction. [21] All models include NYMEX implied volatility and the load-weighted capacity price.

Each model provides a 2SLS estimation. Parallel OLS reduced-form models with no endogeneity correction for auction competitiveness are provided in Appendix B. Comparison with the OLS results highlights the practical importance of treating competition as endogenous and demonstrates functional differences in the competition variable coefficient in terms of magnitude and standard error. It also reveals differences in other key variables, namely capacity and tranche volume. As such, we consider the 2SLS models more reliable. Competitiveness is operationalized as the count of losing bidders in all below models. Models using registered bidders instead, are highly similar though slightly less robust and less theoretically consistent with the competitiveness construct.

In all models, the competition variables are highly internally consistent in coefficient magnitude and standard errors. This indicates that, for each additional losing bidder, the auction clearing price declines by about \$3.50/MWh. Across all models, this is statistically significant by at least $p<0.1$. This provides some confirmation of the common intuition that greater competition among bidders in procurement auctions results in retail prices that reflect a smaller markup above the wholesale price.

The effect of competition on this markup is pronounced. Figure 1 presents predictive margins from Model 1 for the interquartile range of the wholesale forward energy prices (\$31/MWh and \$41/MWh, respectively), and also for the interquartile range of losing bidders (4 and 7 losing bidders, respectively). The predictive margins are statistically significantly different at $p<0.05$. The retail auction price markup at the 25th percentile of wholesale price changes from a 79% markup with only 4 losing bidders, to a 43% markup with three additional losing bidders. At the 75th percentile of wholesale price, the retail auction price markup with only 4 bidders is 47.9%, but with 7 bidders it is reduced to 20.24%. In other words, under

[21] Here, we report wholesale electricity models using natural gas implied volatilities, and do not report results using West Hub implied volatilities because omitted years in ICE data raise robustness concerns. Results of unreported models using West Hub implied volatilities, however, are similar. The pairwise Pearson correlations between the implied volatilities of NYMEX and West Hub as of the dates of the auction is 44.96%.

most wholesale market price scenarios, auction involvement by as few as three additional competing bidders can reduce the retail price markup by 27 to 36 percentage points.

The results also suggest that the quantity of tranches for sale, which is set in advance of the auction (see Appendix A), plays an important role in reducing auction price. Its betas are all between 25.3 and 31.6 ($p<0.05$), which suggests that for each additional 10 percent of the total SSO load obligation that is auctioned, clearing prices fall by between \$2.53/MWh and \$3.60/MWh. At the mean of tranche volume (between 20 and 25 percent) the gas models predict auction clearing prices between about \$53/MWh and \$55/MWh. Taken together with the results from the volume of bidders, the results confirm intuition (Klemperer, 2002; Milgrom, 1989; Milgrom & Weber, 1982; Selten, 1973) that more liquid auctions with a greater number of competitors competing over a larger procurement volume result in more efficient prices. Note that tranche volume is exogenous and very weakly correlated with the count of losing bidders ($\rho=0.25$) and the count of registered bidders ($\rho=0.05$).

The results indicate that capacity price also plays an important signaling role in auction outcomes. This finding is consistent with feedback provided by active wholesale market traders with whom we engaged during data gathering. The load-weighted capacity cost coefficients are between 0.84 and 0.98 in the gas models and all are significant at $p<.01$. These coefficients indicate that a capacity cost increase of about \$4/MWh (a standard deviation) results in a \$3.60/MWh increase in the retail auction price. Marginal predictions holding all other variables constant at their mean indicate that a change from the mean of \$10.59 to the 75th percentile at \$13.41 would result in a retail auction clearing price increase of approximately \$1.875/MWh.

Implied volatility is also a robust predictor at $p<0.05$ or better, with coefficient magnitudes between 0.17 and 0.29. These suggest that an increase of 10 units in the 30-day ATM implied volatility increases the auction clearing price by about \$2/MWh to \$3/MWh. The marginal prediction holding other variables constant at their mean indicates that a change from the 25th percentile (an implied vol of 34.4) to the 75th percentile (an implied vol of 52.3) raises the auction clearing price by about \$5/MWh (from about 50 to about \$55). The magnitude and statistical robustness of this variable's coefficient suggests that factors that are less easily hedged by bidders command a risk premium that directly impacts retail prices to consumers. Suppliers thus inflate their bids to pass on this risk to consumers.

Most intuitively, the underlying commodity price of natural gas is a key predictive factor. Coefficients for gas price differ between current and forward gas prices as of the day of the auction, with forward price increases commanding considerably larger retail auction price increases than current gas prices. While all gas price coefficients are significant at $p<0.01$, coefficients for current prices as of the day of the auction are approximately 5.4, whereas coefficients for gas forwards are approximately 7.3 (35% higher). Both gas forward and current NYMEX prices are not statistically different at the mean ($t=0.95$, $p<0.339$).

However, they are considerably different in variance. The standard deviation of gas forwards is 27.5% smaller than the standard deviation in the current NYMEX price ($p<.01$ on a two-sample variance ratio test), indicating that the gas forwards capture less underlying volatility. Holding all other variables constant at their mean, a change in the current gas price from $2.5/MMBtu to $5/MMBtu results in a retail auction clearing price increase of $13.70/MWh (from $49.85/MWh to $63.55/MWh). That same change from $2.5/MMBtu to $5/MMBtu in the forward gas price results in an $18.28/MWh increase in the auction clearing price (from $47.47/MWh to $65.75/MWh). Given this, retail auction prices are 33 to 35% more responsive to the more stable and lower volatility gas forwards than the current, fluctuating NYMEX price on the day of the auction. This suggests that auction bidders are more responsive to future price fundamentals than prevailing conditions at a single point in time.

Finally, load is not statistically different from zero in any models. SSO load is generally predictable and rather easily hedged, and presents no additional retail price markup. Load is also rather stable across the ten-year duration of this study.

The results can also be utilized to quantify the marginal impact on retail auction price markups above the wholesale price. At the mean and holding all other variables constant at their mean, Model 1 predicts a retail auction price markup of $15.67/MWh (or 40.7%) above the wholesale market forward price. At the interquartile range of the wholesale forward energy prices ($31/MWh and $41/MWh, respectively), Model 1 predicts markups of \$19.36/MWh (62.4%) and \$14.41/MWh (35.1%). Because the coefficient on the wholesale price forward is less than 1, retail auction price markups decline with increasing wholesale electricity price forwards. Even at the highest quartiles of wholesale prices, however, the markup is well above 30%.

Implied volatility also has pronounced effects on retail auction price markups. Figure 2 presents predictive margins for Model 1 for the 5th and 95th percentiles of the NYMEX gas implied volatility metric described above (at implied volatilities of 24 and 91). In low wholesale electricity price forward markets (at \$29/MWh), that change in implied volatility results in a 41% increase in the retail price. In high wholesale price forward markets (at \$61/MWh), this change in implied volatility results in just under a 30% increase in the retail auction clearing price.

Considering the impact of both competition and implied volatility on retail auction price markups can also be helpful in illustrating results. Figure 3 presents predictive margins plots for the 5th to 95th percentile range of the Total On- and Off-peak Load-Weighted Forward Price, with predictive margins presented separately for the 5th and 95th percentile of NYMEX implied volatility. The panels in Figure 3 separately present the 25th and 75th percentiles of the competition variable losing bidders. This range of implied volatility adds approximately \$15/MWh to the retail auction price. However, the additional competition in the form of three additional bidders has approximately the same effect as a 90-percentage point increase in volatility (see the delta in the common Y-axis). Comparing the coefficients between competition and implied volatility, a single additional bidder has approximately the same retail price savings effect as a 14-point decrease in implied volatility (which is just under a single standard deviation).

These effect magnitudes can be put into greater perspective by comparing the competition results to the impact of the US Shale Boom. Between 2008 and 2016, the net annualized NYMEX Henry Hub price declined from \$8.86/MMBtu to \$2.52/MMBtu (a \$6.34/MMBtu decrease) according to the EIA. The models presented here estimate that this same change would be the equivalent of a \$34.74/MWh (3.4 cents/KWh) decrease in the retail auction prices ultimately passed on to SSO customers, holding all other variables constant at their mean. This same magnitude of retail electricity price savings is equivalent to the estimated savings associated with 9 additional bidders in these procurement auctions. Put another way, increasing the competitiveness of the procurement auctions by less than doubling the number of bidders could have net consumer impacts of approximately the same size and magnitude as the Shale Boom. The importance of competition should not be understated.

Table 4. Auction Clearing Price Regression Models (based on wholesale electricity inputs)

Auction Price	Model 1	Model 2	Model 3	Model 4	Model 5
Losing Bidders	-3.784** (1.609)	-3.710** (1.556)	-3.555** (1.551)	-3.832** (1.569)	-3.881** (1.622)
Tranches for Sale	-30.036** (12.410)	-27.028** (12.623)	-26.846** (12.218)	-28.812** (12.779)	-31.622** (12.209)
Total On- and Off-Peak Load-Weighted Mean Forward Price	0.505*** (0.157)				
Forward On-Peak Mean Price		0.651*** (0.144)			
Load Weighted Forward On-Peak Mean Price			0.583*** (0.138)		
Forward Off-Peak Mean Price				0.806*** (0.212)	
Load Weighted Forward Off-Peak Mean Price					0.345 (0.220)
Load Weighted Capacity Cost	0.946*** (0.315)	0.968*** (0.286)	0.992*** (0.297)	0.955*** (0.303)	0.900*** (0.329)
NYMEX Implied Volatility	0.267*** (0.069)	0.232*** (0.066)	0.240*** (0.065)	0.251*** (0.068)	0.293*** (0.072)
Log On-Peak Load (Billions MWh)		0.818 (1.646)			
Log Off-Peak Load (Billions MWh)				0.748 (1.721)	
Constant	58.327*** (19.144)	29.085 (48.413)	49.628*** (18.892)	33.558 (51.086)	67.785*** (19.302)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Utility Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.797	0.818	0.821	0.803	0.781
First-stage Instrument					
Switching Rate	0.188*** (0.051)	0.185*** (0.051)	0.184*** (0.051)	0.187*** (0.051)	0.193*** (0.051)
F-statistics for IV in first stage	13.85	13.41	13.31	13.74	14.44
N	120	120	120	120	120

Notes: 2SLS regression models with robust standard errors in parentheses (*** *p<0.01*, ** *p<0.05*, * *p<0.1*).

Table 5. Auction Clearing Price Regression Models (based on natural gas inputs)

Auction Price	Model 6	Model 7	Model 8	Model 9
Losing Bidders	-3.715** (1.600)	-3.717** (1.600)	-3.014* (1.658)	-3.017* (1.658)
Tranches for Sale	-25.294** (12.886)	-25.327** (12.892)	-25.248* (13.131)	-25.284* (13.134)
NYMEX Henry Hub Price	5.480*** (1.423)	5.475*** (1.422)		
Forward NYMEX Price Mean			7.311*** (2.235)	7.302*** (2.232)
Load Weighted Capacity Cost	0.987*** (0.287)	0.986*** (0.288)	0.842*** (0.282)	0.841*** (0.282)
NYMEX Implied Volatility	0.169*** (0.065)	0.169*** (0.065)	0.239*** (0.065)	0.239*** (0.065)
Log On-Peak Load (Billions MWh)	0.027 (4.624)		0.147 (1.435)	
Log Off-Peak Load (Billions MWh)		-0.024 (1.628)		0.091 (1.433)
Constant	64.284 (45.197)	65.523 (45.251)	34.976 (46.085)	36.365 (45.901)
Year Fixed Effects	Yes	Yes	Yes	Yes
Utility Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.812	0.811	0.838	0.838
First-stage Instrument				
Switching Rate	0.184*** (0.050)	0.184*** (0.050)	0.176*** (0.049)	0.176*** (0.049)
F-statistics for IV in first stage	13.94	13.93	13.25	13.23
N	120	120	120	120

Notes: 2SLS regression models with robust standard errors in parentheses (*** *p<0.01,* ** *p<0.05,* * *p<0.1*).

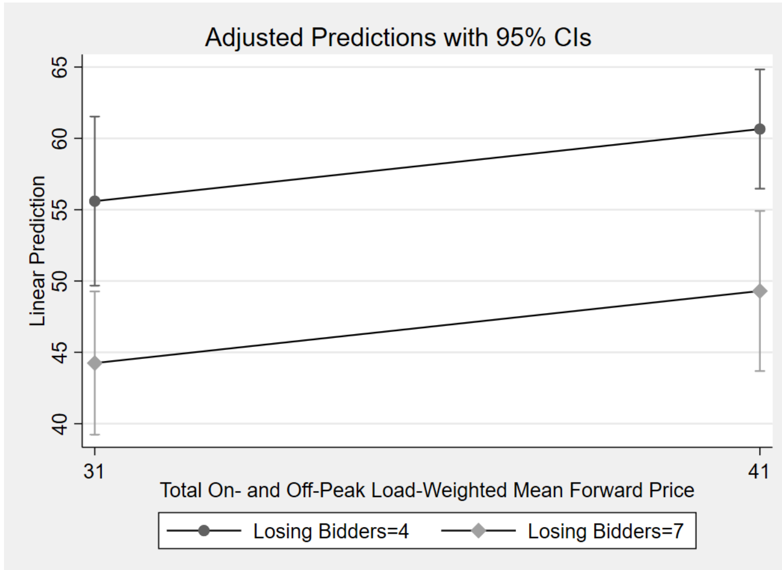

Figure 1. Effect of Auction Competition on Price Markups

Note: Marginal y-hat predictions based on Model 1 at the inter-quartile range of losing bidders and Total On- and Off-Peak Load-Weighted Mean Forward Price.

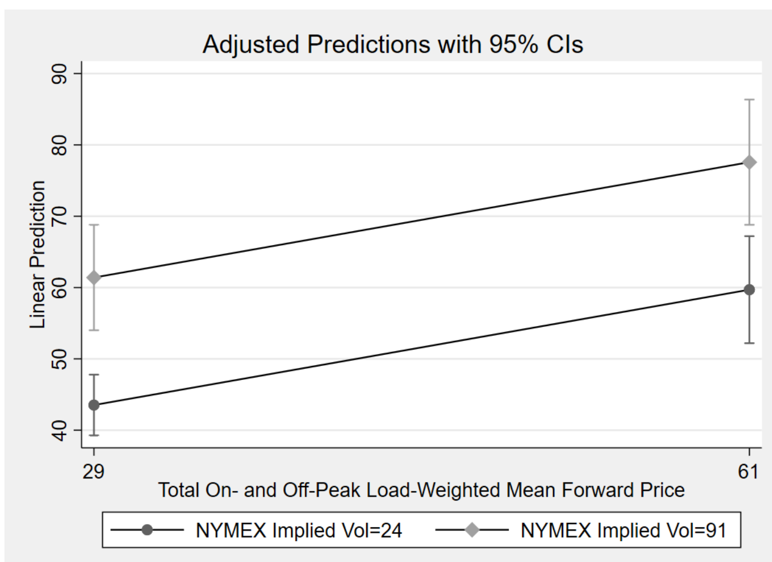

Figure 2. Effect of Implied Volatility on Price Markups

Note: Marginal y-hat predictions based on Model 1 at 5^{th} and 95^{th} percentile of Total On- and Off-Peak Load-Weighted Mean Forward Price and NYMEX Implied Volatility.

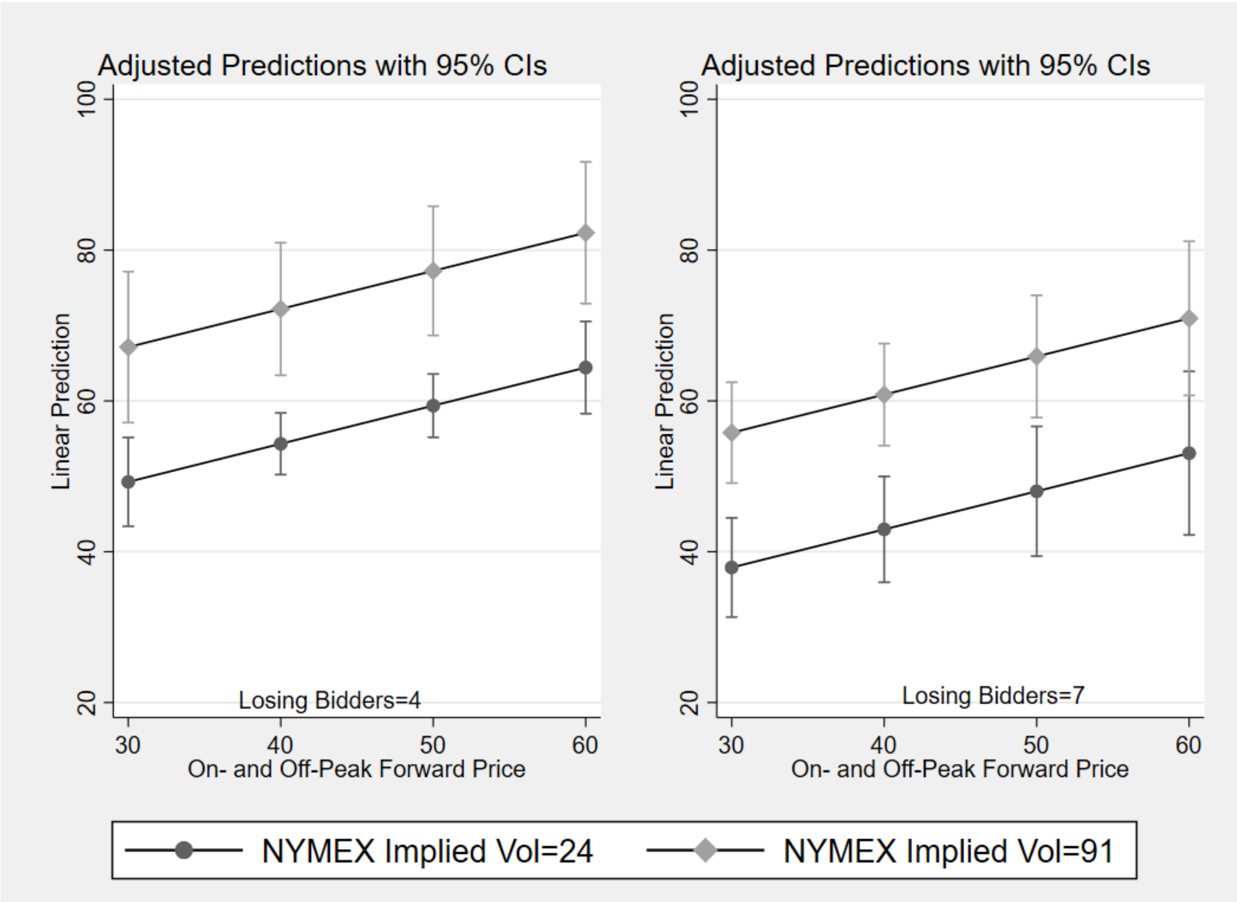

Figure 3. Effect of Competition and Implied Volatility on Price Markups
Note: Marginal y-hat predictions based on Model 1 at 5th and 95th percentile of NYMEX Implied Volatility and 5th to 95th percentile range of Total On- and Off-Peak Load-Weighted Mean Forward Price incremented by ten. Left panel predictions based on 4 losing bidders (25th percentile). Right panel based on 7 losing bidders (75th percentile).

7. Conclusions and Policy Implications

We have presented and analyzed a comprehensive dataset to study the determinants of retail electric generation prices for default service customers in a retail restructured state. Using this dataset, we evaluate every historical SSO auction for each of Ohio's four electric distribution utilities over a decade. Econometric results indicate that retail prices are not simply influenced by the wholesale market, but that the retail price markup above the wholesale cost is driven significantly by two main sets of factors.

First, the competitiveness of the auction plays a considerable role. Less competitive auctions result in inflated retail prices significantly above the underlying cost of a supplier's full-requirements obligation. We find that the retail generation price is typically marked up by about 40 percent above the forward wholesale electricity price, and that even slight changes in competitiveness (i.e., when as few as 3 suppliers do not bid) can essentially double this markup from 40 to 80%. Ultimately, the volume of competing bidders plays a striking role in delivering competitive retail prices to end consumers.

Second, we find that retail price markups are driven by wholesale market characteristics that are less easily hedged by suppliers. We find that the volume of load in procurement is not a statistically significant indicator of price, likely because it can be readily hedged. By comparison, we also find that implied volatility and forward market electricity price volatility significantly inflate retail price markups. Across varying market conditions, increases in the 30-day ATM implied volatility can inflate retail generation prices by anywhere between 30 and 41 percent. Because implied volatility indicates increasing supplier risk, that translates to a considerable risk premium that is passed on to consumers in the resultant retail price. Additionally, because the forward price of natural gas has a significantly lower volatility than the current or spot price, we find that retail markups are significantly more responsive to volatility increases in price forwards. In other words, when the price forwards (which are generally more stable than current prices) increase in volatility, consumers can expect significantly larger risk premia in the form of higher retail prices passed on to them through the auctions that set the default service price, and that highly influence third-party retail supply offers.

Additionally, we confirm expectations that retail prices are predominantly influenced by underlying input commodity prices, including the future wholesale hub price of electricity, the price of natural gas, and the load-weighted regional capacity cost. Each of these costs should, and do, form the basis of an efficient retail pricing construct. The additional markup on top of these costs, however, is driven by the above-mentioned factors.

These results have important implications for future research. While prior research has focused predominantly on evaluating the efficiency of wholesale markets and wholesale market design, our findings necessitate increased, if not equal, attention to retail market design. And, because the SSO price is a price heuristic that influences competitive prices in states with retail choice, future research is needed to understand the full extent of these retail market design implications. This can include price signaling or strategic behaviors, such as SSO price markups increasing permissible CRES markups. This can also include strategic behaviors among suppliers acting jointly in both CRES and SSO markets, such as strategically exiting the SSO auction to extract additional rents from CRES markups.

Future research is also needed to evaluate the most efficient auction format for retail electricity procurement. In Ohio and many other states using similar auction-based procurement, very little empirical research was performed or relied upon prior to the implementation of the current auction format, and prior to important decisions to use the current system of layered tranches and lengthy forward maturities. Our results suggest that future research can play a meaningful role in helping to potentially modify and improve auction design and bidding rules, similar to the extensive auction design efforts employed in multiple other domains, including the US Title IV Acid Raid Program (Cason & Plott, 1996; Ellerman et al., 2000; Franciosi et al., 1993; Hahn, 1984; Hahn & Noll, 1983), wholesale electricity markets (Kahn et al., 2001; Staropoli & Jullien, 2006), the FCC's spectrum auctions (Banks et al., 2003; Weber, 1997), and carbon markets (Burtraw et al., 2009; Dormady, 2013, 2014a; Dormady & Healy, 2019; Godby, 2002; Holt et al., 2007; Tietenberg, 2006). And, our results suggest that factors such as tranche size and forward maturity, which are within the control and discretion of regulators, auction managers and other key stakeholders, can be adjusted and modified within a transparent procurement process to further improve retail efficiency.

Finally, this study motivates key public policy implications on a very timely topic for many US states. Multiple states have initiated regulatory and/or legislative proceedings to revisit or significantly modify their retail pricing mechanisms. Much of the reform push has been driven by misconduct on the part of third-party retailers. See e.g., Baldwin and Felder (2019) or Dormady et al. (2024) for detailed summaries of regulatory and criminal misconduct case histories. In some jurisdictions, reforms include actions to make default service universal for disadvantaged customers or all residential customers. Maryland recently capped third-party supplier offers at the default service price, similar to Australia's policy, which Esplin et al. (2020) found to be distortionary. New York recently imposed effective price caps on retail supply offers, requiring ex post customer refunds if realized prices exceed the default price. And, in a new stipulation agreement in the PECO service territory in Pennsylvania, terminated retail contracts would be rolled back to default service upon contract expiration, and a large graphic with the default price alternative would be displayed on consumer bills, among other major reform proposals. Similar modifications have been implemented in Massachusetts and Maine. Each of these proposals or reforms illuminates the societal criticality of understanding the underlying mechanisms that influence the default price. And they highlight the important role that default prices play in signaling and influencing all other retail prices.

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