What are the Benefits to Flexible Regulatory Mechanisms? Evidence from the Electricity Market

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Abstract

Theory often shows that more flexible industry regulation should increase welfare relative to rigid regulation. However, quantifying the economic benefits to such flexibility is difficult. We take advantage of the exogenous change in the price of natural gas between 2005 and 2011 resulting from technological innovations in extractive industries like hydraulic fracturing to identify the benefits of regulatory flexibility in the electricity sector. We model an electricity purchasers’ (e.g., utilities) problem in the face of load uncertainty when given the regulatory flexibility to purchase electricity from multiple markets: both the day ahead and real time markets. The model predicts that changes in the cost of supplying electricity on the real time market should lead to predictable changes in the fraction of quantity purchased on the real time market. We estimate the date of the structural break in natural gas prices using a Markov Switching Model. Using data from the PJM wholesale electricity market, we test the model’s prediction across the high natural gas price versus low natural gas price regime. We find behavior consistent with the model. We estimate cost savings from this flexible regulatory structure are around $1.2 billion/year within PJM.

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1 Introduction

Much government intervention in the economy attempts to reduce uncertainty. Unemployment insurance, price floors or ceilings in newly created exchanges, and disaster relief funds are three notable examples. In each case, the uncertainty reduction intended by government intervention takes a different form. In some cases there is incomplete information leading to uncertainty that will eventually be revealed through repeated transactions [Joskow et al. (1998)]. In others there is some element of irreducible uncertainty, such as with weather events.

It is desirable that the government mechanisms designed to reduce uncertainty be flexible enough to efficiently adapt to uncertain or changing market conditions. One example of a rigid government mechanism is unemployment insurance; regardless of the state of the macroeconomy, the maximum length of benefits that can accrue to a recipient is fixed. Indeed, there is extensive economic literature which catalogues the inefficiencies created by such inflexibility of government policy and not allowing regulated prices or quantities respond to market conditions (see [Heutel (2012) or Kelly (2005)]). It seems less frequent to observe a well-functioning federally administered or regulatory institution designed to adapt to changing market conditions.

This paper considers the design and response of a federally commissioned entity to a fundamental change in market conditions in the face of uncertainty. Specifically, we consider how wholesale electricity purchasers used regulatory flexibility afforded them by Regional Transmission Operators (RTOs) to respond to cheap and abundant natural gas used in generation from 2009-2011. The operators are tasked with matching total electricity supplied from all generators to total electricity demanded by electricity users. We argue that grid operators face constant and irreducible uncertainty due to unpredictable weather patterns affecting demand. We find that due to the mechanism used to operate this market, operators are able to, and do efficiently, let market participants respond to decreased natural gas prices
in surprising but efficient ways.

The Federal Energy Regulatory Commission (FERC) oversees electricity RTOs that facilitate the electrical grid. An RTO must predict total electricity demand every hour of every day and then facilitate that level electricity to be supplied by electricity producers. To do this, potential sellers of electricity (e.g., power plants) bid for the right to produce at a forecasted level of demand the following day. While the RTO makes a public forecast of electricity demand, actual total demand from electricity purchasers like utilities may be somewhat different. Importantly, then, electricity purchasers are allowed the flexibility to purchase any whatever quantity they want on the day ahead market by their regulator. This market, known as the day ahead market for electricity, clears each day. However, there are inevitably forecast errors in the level of expected demand due to unexpected realized demand shifters such as weather. As a result, there is also a real time market for electricity which occurs when there is full information regarding realized demand levels. In effect, then, the real time market acts as a call option to meet unexpected demand. The real time market is essential to facilitate production since final user electricity demand is inelastic to wholesale price changes (Borenstein (2002) and Borenstein et al. (2002)).

When natural gas prices dramatically fell in 2009 due to increased use of horizontal drilling and hydraulic fracturing, it fundamentally changed the cost of providing electricity over the entire load profile. It is reasonable to expect, then, that the cost of meeting unexpected load on the real time market changed as well. We show that the decrease in natural gas prices asymmetrically affected the cost of meeting unexpected load, or what we call the “short run elasticity of electricity supply”. A change in the short run supply elasticity changes the cost of meeting unexpected demand. Put another way, as the short run supply elasticity decreases, the price of the call option (the price on the real time market versus the day ahead market) falls, and vice versa. We show in a simple theoretical model that a strategic electricity purchaser will buy less on the day ahead market when the short run elasticity decreases and more when the short run elasticity increases given the regulatory
flexibility to do so. As a result, one would expect a significant increase in the proportion of actual load that is purchased on the day ahead market if there is a increase in the short run elasticity of supply.

We use non-parametric techniques to estimate the short run supply of electricity, how it changed in response to the fall in natural gas prices, and the subsequent response of electricity purchasers. First, we identify the date of the structural break in natural gas prices in the late 2000’s using both a Markov Switching model and a rolling Chow test. We then estimate the short run elasticity of electricity supply over different load levels. Given retail rate structures in electricity markets, we employ the common assumption that short run electricity demand is inelastic to identify supply (Borenstein (2002) and Borenstein et al. (2002)). Using publicly available data on day ahead and real time prices and day ahead and real time load from a very large RTO on the east coast of the US, PJM, we estimate the short run elasticity of supply and changes in the composition of load purchased on the day ahead from real time market. We find that the decrease in natural gas prices affected short run elasticities, sometimes in unexpected ways, and that electricity purchasers reacted as predicted by the theoretical model.

To identify the benefits of allowing electricity purchasers the flexibility to change the composition of their electricity purchases on the day ahead and real time market as a function of price (e.g., the short run elasticity of supply) we perform simulations. We find simulate a years worth of hourly load observations and prices subject to distributions estimated from the data. We then compare the costs of meeting load as observed for each electricity regimes: both the high elasticity regime (e.g., regime 1) and the low elasticity regime (regime 2). We then simulate the costs of meeting load in regime 2 if the RTO were forced to continue to meet demand by purchasing from the day ahead and real time markets as they did in regime 1. We find that such rigid regulation would cost an extra $1.2 billion/year within PJM, or 4.2% of total wholesale electricity expenditures.

There are several contributions of these findings. First, we are able to characterize
the effect decreased natural gas prices on the understudied difference in the day ahead versus real time electricity market. Second, we contribute to the literature recognizing the importance of the strategic behavior of the electricity market participants, albeit along a slightly different dimension: across time as opposed to across firms (Bushnell et al. (2008) and Mansur (2008)). Third, we are able to demonstrate that the flexibility afforded to RTOs by their regulatory agency enables them to significantly increase welfare allowing electricity purchasers to respond to market conditions. As a result, we argue that allowing government policy designed to mitigate uncertainty to respond to changing market conditions is vital to increase economic efficiency.

The paper is organized as follows: section 2 offers background on both natural gas prices and the PJM RTO. Section 3 introduces a simple theoretical model. Section 4 conducts the main empirical estimation procedures including the simulations. Section 5 concludes.

2 Background

2.1 Cheap Natural Gas

Technological advances in extractive industries, most famously horizontal drilling and hydraulic fracturing, have been associated with large price declines in natural gas. Horizontal drilling methods allow a well to be drilled down for hundreds or thousands of feet then turned at a nearly ninety degree angle. This procedure permits as many as eight wells to be drilled for the same pad. Hydraulic fracturing involves injecting hydraulic fluid into a well to break rock formations rich in hydrocarbons which then rise up the well shaft to the surface where they can be collected. These new extraction techniques make it possible to remove small pockets of gas that were previously considered unrecoverable. Shale, a porous stone formed by layers of clay, is a particularly rich source of these pockets of gas and large regions of shale close to the surface (known as shale plays) have become a source for a large
and growing fraction of natural gas in the U.S. market.

Figure 2 displays the time series of natural gas prices from 1994-2012. After decades of low prices, increases in installed natural gas generation led to increase natural gas prices in the early 2000’s. Prices climbed steadily until late 2008 and early 2009 when reduced demand due to the recession and increased supply from shale plays.

While we leave our discussion for how we handle different economic conditions to the main empirical section, we address the increase in the supply of natural gas here. An increase in natural gas production happened in 2008 when the fall in natural gas prices. Figure 3 describes the annual number of production-days at all natural gas wells in Pennsylvania, one of the largest producers of shale gas and one of the few states to provide detailed production data. Production increases in 2008 and continues at that high level through 2010. There are two important features in the figure. First, the flow of natural gas is a function of the stock of previously existing wells that continue to produce gas and new wells. As result, the additional wells were likely producing at relatively higher levels than the pre-existing wells. Second, the increase in well production days was over 33%. This is likely a lower bound on the total increase in natural gas produced in Pennsylvania, though, since the newer wells were producing at higher levels.

2.2 PJM Market Structure and Data

We focus on PJM an Integrated Systems Operator (ISO) that manages, but does not own, the electricity transmission network. Under electricity market deregulation, Regional Transmission Operators (RTO’s) were created to manage markets and coordinate delivery of wholesale electricity and PJM became the nation’s first operating RTO in 2001. PJM initially encompassed only Pennsylvania, New Jersey and Maryland but has expanded steadily to cover thirteen states and the District of Columbia. The electricity suppliers in the region form a
single supply pool and consumers’ demand can (theoretically) be served by the lowest cost supplier anywhere in the pool. For PJM’s case this supply pool is currently nearly 185,000 MW and provides electricity for more than 60 million people. The RTO is charged with managing the market that balances supply and demand throughout their region.

The ISO operates two markets to find equilibrium price and quantity for each hour of each day. The day ahead market which closes at noon on the day before delivery and a real time market that balances supply and demand and transacts throughout the day. PJM is a nodal market meaning that electricity can be bought and sold at thousands of points in the region. In the day ahead market generators are required to bid an upward sloping supply schedule describing their willingness-to-accept and consumers provide corresponding demand curves. The RTO then solves for the market clearing price at each node in the system, using the physical relationship of the grid to solve for prices where there were no bids. This process takes about four hours and the results of the day ahead market are posted sometime around 4PM. Generators with unsold capacity are then permitted to sell into the realtime market which transacts hour-by-hour the next day. Consumers whose demand for electricity differs from what they secured in the day ahead market can either sell excess or cover shortfalls through this market. The vast majority of electricity demand is satisfied through the day ahead market with the real time market used primarily to respond to unexpected deviations in real time consumption. Examples include transmission line outages, power plant malfunctions and unexpected weather conditions.

The bidding process for the PJM RTO is complicated by irreducible uncertainty associated with these unexpected events. PJM forecasts demand according to a well-defined function relating weather, time/day/monthly fixed effects and economic variables. However, demand in any time period is uncertain until all weather variables have actually been realized. As a result, there is both a day-ahead market and a real-time market to facilitate matching electricity supply to electricity demand. For example, to meet load on June 2 bidding on the day ahead market occurs on June 1. PJM then allocates production on June
1st based upon its forecast of electricity demand to the lowest cost producers for production on June 2nd.\footnote{On June 2nd, actual weather variables are realized and if they are sufficiently different from forecast, then actual electricity demand may differ from forecasted demand. As a result, the same bidding process takes place again on June 2 to meet any additional demand for electricity that results from incorrectly forecasted demand.}

It is very reasonable that cost of providing electricity on the real time market is fundamentally different than providing it on the day ahead market. First, different fuel types can quickly scale up or down production at varying cost levels. For example, natural gas and oil generation is often thought to be more easily ramped up and down that coal. Second, there is heterogeneity in how easily plants can quickly scale up or down production within each fuel type. Third, the interaction of plants already dispatched to provide at expected total load levels and those need to meet unexpected demand can influence the marginal cost of the available remaining capacity on the spot market. We aim to isolate how regulatory flexibility took advantage of the change in natural gas prices due to increased supply affected the cost of supplying electricity on the real time market— the short run elasticity of supply— in this paper.

### 3 Theoretical Model

From the perspective of electricity purchasers, it is not necessarily optimal to purchase the point forecast of expected electricity demand on the day ahead market. The real time market offers a hedge against unexpectedly high load demand while permitting a purchase to not have to buy un-needed electricity should demand be unexpectedly low. The cost of meeting additional demand on the real time market, the short run elasticity of supply, is a key parameter determining the optimal mix of purchases on the real time versus day ahead market. The short run elasticity of supply is the percent increase in cost of electricity for a
one percent increase in production from the amount cleared in the day ahead market. This section constructs a simple theoretical model showing how the composition of electricity production should vary across the day ahead and real time market as a function of economic variables.

While tempting to model the electricity purchaser’s problem an optimal portfolio allocation issue with both a long position (the day ahead market) and a call position (the real time market), it is not practical due to the nature of our study. The price of a call option is determined by the stock price’s irreducible uncertainty at the time the call option is purchased. However, we are identifying and modeling the effect of an exogenous decrease in the short run elasticity of supply (e.g., the call option) due to input price changes conditional on no change in the irreducible uncertainty. As a result, we model the problem as a simple two period cost minimization problem.

The electricity purchaser’s problem is to minimize costs of total expenditures used to purchase a given amount of realized demand, $Q$. The electricity purchaser forms a forecast of realized demand, $\hat{Q}$, which is normally distributed around the true realized demand. As a result, realized demand is a normally distributed random variable: $Q \sim N(\hat{Q}, \sigma^2)$. Total cost of provision within each period is convex in production within each period. The electricity purchaser’s cost minimization problem is:

$$\min_{Q_r, Q_d} TC_d(Q_d) + E[TC_r(Q_r|Q_d)]$$

$$Q_r + Q_d = Q, \quad Q \sim N(\hat{Q}, \sigma^2)$$

$$\Rightarrow \min_{Q_d} TC_d(Q_d) + E[TC_r(Q - Q_d|Q_d)]$$

In this problem, there are two cost curves: the day ahead cost curve $TC_d(Q_d)$ and the real time cost curve, $TC_r(Q_r|Q_d)$. Note that the real time cost curve is conditional on a certain elasticity.
level of demand purchased on the day ahead market. This modeling decision is based on the fact that different power plants pay different costs of quickly ramping up generation even withing their own generation profiles. Also, at time of purchase on the day ahead market, costs on the day ahead market are perfectly known. As a result, the expectations operator only operates on the realtime market since actual demand in any hour is a random variable.

In this model, the electricity purchaser’s first order condition is:

\[ MC_d(Q^*_d) = E[MC_r(Q - Q^*_d)|Q^*_d]. \]  

Equation (1) equates expected marginal costs across the day ahead and real time markets.

We now introduce a simplifying assumption that greatly eases comparative statics: assume that marginal costs are locally linear. Specifically, assume that around \( Q^*_d \) that \( MC_d = c \) where \( c \) is allowed to vary with \( Q^*_d \). Without loss of generality, \( MC_r = \alpha c \). Thus, \( \alpha \) can be interpreted as the slope of the short run marginal cost curve relative to the regular marginal cost curve. The graphical interpretation of this set up is shown in Figure 1. If the point forecast of demand at a particular time were \( \hat{Q} \) and the market demanded \( Q \) units of electricity in the day ahead market, in the subsequent real time market electricity purchasers would have to buy subject to the short run marginal cost curve \( MC^0_{SR}(Q) \).

The main comparative static of interest is the effect of a change in relative slopes of the day ahead and real time marginal cost function on relative electricity purchases between the day ahead and real time market: \( \frac{d^2 \hat{Q}}{d\alpha} \). We assume throughout that forecasts are not biased.

The last step in setting up the electricity purchaser’s problem is to accurately write down the conditional marginal cost function in the real time market. To do so, we can write the first order condition of the electricity purchaser in its explicit form:

\[ cQ^*_d = \alpha c \int_{Q_d^*}^{Q_{max}} (Q - Q^*_d)f(Q)dQ + \gamma c \int_{Q_d^*}^{Q_{min}} (Q^*_d - Q)f(Q)dQ. \]

The left hand side of the complete first order condition is the marginal cost of purchases.
in the day ahead market. The first term on the right hand side is the expected additional marginal cost incurred on the real time market conditional on realized demand being greater than the amount purchased in the day ahead market. The second term on the right hand side is the cost of purchasing too much on the day ahead market. When a purchaser buys too much on the day ahead market they become a seller on the real time market. This does occasionally occur in practice. When it does, it is always the case that there is an abundance of electricity and the price in the real time market falls below the market clearing price on the day ahead market. In fact, the real time price of electricity can sometimes become negative as real time electricity sellers must pay other market participants to take electricity. As a result, we make the assumption that $\gamma < 1$. This assumption means that when realized demand is below the amount purchased in the day ahead market that market clearing price for electricity in the real time market is below the market clearing price in the day ahead market from the previous day. We can then implicitly differentiate the first order condition and simplify to get the main comparative static of the theoretical model:
\[
\frac{dQ^*_d}{d\alpha} = \frac{\int_{Q^*_d}^{Q_{\text{max}}} Q f(Q)dQ - Q^*_d \int_{Q^*_d}^{Q_{\text{max}}} f(Q)dQ}{1 + \alpha \int_{Q^*_d}^{Q_{\text{max}}} f(Q)dQ - \gamma \int_{Q_{\text{min}}}^{Q^*_d} f(Q)dQ} = \frac{E[Q|Q > Q^*_d] - Q^*_d(1 - F(Q^*_d))}{1 + \alpha - F(Q^*_d)[\alpha + \gamma]} > 0
\]

By inspection, the numerator is positive. Given the assumption that \( \gamma < 1 \), the denominator is also positive. As a result, \( \frac{dQ^*_d}{d\alpha} > 0 \): if purchasing electricity on the real time market become more expensive then cost minimizing purchasers will buy relatively more on the day ahead market for any given level of forecasted demand, \( \hat{Q} \). There are two hypotheses which follow immediately. First, if real time production becomes relatively more/less expensive, then the percentage of electricity purchased on the day ahead market will increase/decrease. A second related hypothesis is that observed forecast errors by RTOs, \( Q - Q_d \), should increase if \( \alpha \) decreases as electricity purchasers consistently purchase more electricity on the real time market if real time electricity is cheaper to purchase.

Note that the SR elasticity is measured as a percentage of a price change. As a result, if the day ahead market clearing price for electricity were $50 and the SR elasticity were 5\%, then the price of electricity purchased on the real time market would be $52.50. Similarly, if the day ahead market clearing price for electricity were $100 and the SR elasticity were 5\%, then the price of electricity purchased on the real time market would be $105. As a result the actual dollar amount of the same SR elasticity varies over the supply curve. As a result, the cost of having to purchase electricity on the real time market is a function of both the SR supply elasticity and the wholesale electricity price. As a result, any analysis must allow both parameters to vary.

In sum, there are two testable hypotheses based upon this very simple theoretical model. First, for any load levels for which the real time supply curve shifts down, relatively more power should be purchased on the real time market. Second, for any load levels for which
the real time supply curve shifts down, observed forecast errors of the RTO will decrease as they begin to purchase less electricity on the day ahead market. We test the first hypotheses in the next section since it is the hypothesis directly related to regulatory flexibility and address the forecast error hypothesis in an appendix.

Important before proceeding and for interpretation of the results in our model is considering vertical relationships and market power within the electricity sector. Vertical relationships and market power within the electricity sector have been shown to be important for bidding behavior in certain instances. We abstract from these for the following reasons: first, vertical relationships such as long term supply arrangements between electricity producers and utilities are often long lasting contracts. Our analysis concerns only the medium term effects of an exogenous change in market conditions since we only consider the 33 months after the fall in natural gas prices. As a result, we assume that these relationships constant over the time horizon we consider. Second, market power is important insofar as it can restrict supply and increase prices. Since we are concerned with the effects of a decrease in input price on the composition of output, we are able to identify a lower bound on the effect of natural gas prices insofar as there was consolidation of electricity production over the study window. In sum, the relative short time window of our study implies that vertical relationships are fixed throughout our study and any increase in market power works against our findings of any changes in production due to a fall in input prices.

4 Empirical Specification and Results

This section describes the empirical procedures used to identify the start of the regime of lower natural gas prices, the estimation of short run supply elasticities and the counterfactual simulations to identify the welfare increase due to regulatory flexibility.
4.1 Empirical Specification: Break in Natural Gas Prices

We perform two separate tests for identifying when the era of cheap natural gas prices began. The first is a Markov Switching Model. We collected daily data on Henry Hub natural gas spot prices from a Bloomberg terminal excluding weekends and when the market is closed. To analyze this data, we estimate the following simple switching model:

\[ P_{s,t} = \mu_s + \epsilon_{s,t}, \epsilon_{s,t} \sim N(0, \sigma_s^2) \quad s = H, L \]  

In equation (2), \( s \) indexes the state and \( t \) indexes time. We estimate a two by two matrix of transition probabilities (\( \rho_{ss} \) for \( s = H, L \)) as well. In order to ensure a global maximum, we perform a two dimensional solver in which we assign values for \( \mu_H \) and \( \mu_L \) manually then estimate the other six parameters (\( \sigma_s^2, \rho_{ss} \) for \( s = H, L \)). We then choose the model with the highest log likelihood as the true model.\(^4\)

The results from the Markov Switching Model are show in Figure 4. Top panel shows the price data for Henry Hub spot prices. The second panel shows the standard deviation in the system conditional on the estimated state. The third panel shows the probability of being in each regime. Note that \( t=1 \) is January 1, 2005 and \( t=1000 \) is January 6, 2009. The model selects \( \mu_H = 8.0 \) and \( \mu_L = 4.0 \) as the mean natural gas prices although the log likelihoods are close for nearby parameter values of both parameters in both the positive and negative direction. \( \rho_{11} \) and \( \rho_{22} \) are both precisely estimated at one. The variance across regimes are also both precisely estimated: \( \sigma_H^2 = 4.463, \sigma_L^2 = .368 \). The relatively lower variance in the low price regime confirms the optical test of lower volatility later in the data.

Starting on January 8, 2009, the model is very confident in a sustained period of low gas prices interrupted by a fifty day span around \( t= 1200 \) (e.g., late 2009). Given the low estimated variance in regime two relative to regime one, the model selects prices in this interval to reflect the high price regime. We attribute this increase to seasonal demand for

\(^4\)\text{We employ this method to ensure the search algorithm doesn’t find a local maximum, which is a problem that occurs when this method is not employed.}
natural gas for heating. While more robustness checks are needed, we take the switching model as evidence of a low natural gas price regime beginning in early 2009.

We also perform a rolling Chow test on first differenced spot and futures natural gas prices. We run the first difference of the same sequence of Henry Hub natural gas spot prices on seasonal dummies and a time trend. We then create a dummy variable equal to one if the time period is after the date indicated. Figure 5 summarizes the test statistics and their 95% confidence intervals. There is evidence of a break in prices between March and May 2009.

Taken together, these exercises indicate that the era of cheap natural gas began in the first half of 2009. As a result, we select the first regime, the “high gas price” regime, to run from 2005 through January 7, 2009. We begin the analysis in 2005 to avoid variation in environmental regulation. The Clear Air Interstate Rule (CAIR) Act introduced new environmental regulation for power plants in our study region. The second regime begins on January 8, 2009 and runs through the end of the study period in 2011. As a robustness check, we allow for the low price regime to start on April 1, 2009 in an alternative specification. The differences in electricity generator behavior across these two natural gas price regimes will be the source of quasi-experimental variation that allows us to identify changes in the electricity market and the behavior of producers therein.

One important caveat is that we have not controlled for demand for natural gas in this subsection. The identifying assumption to attribute the fall in natural gas prices is the increase in supply rather than a shift of the demand curve. While we do not control for a shift in the demand curve for natural gas in this subsection, we do control for changes in electricity in the next subsection, which estimates the short run elasticity of supply for

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5 Using six month futures contracts, we find similar evidence.
6 The CAIR Act was litigated for nearly a decade up to and beyond the passage of the act. Discussions with industry sources suggest that generators responded before the act was implemented despite the uncertainty of its legal status. In future work we plan to control for pollution permit prices in the region which should alleviate any concerns from attributing changing electricity generator behavior to natural gas prices rather than environmental regulation.
Recall the main hypothesis we test is whether a change in the SR elasticity of supply will affect the percentage of electricity demanded across the day ahead versus real time markets. This section introduces the estimation procedure and presents results for estimating SR elasticities and the composition of electricity demand.

PJM publishes a great deal of data for market participants. The data include hourly measures of load (demand), day ahead price and real time price. The load and price data are in separate files posted monthly. We employ a web scraping program to automatically download the entire price and load history from PJM and compile a time series of hourly day ahead demand, actual (real time) demand, day ahead price and real time price for each hour from July 1, 2005 through June 30, 2011. While additional data is available, we use these dates for two reasons. First, CAIR legislation was implemented before 2005 which may have changed the relative prices of electricity from coal versus natural gas plants. Second, PJM was a constant size throughout this timeframe. As a result, the geographical footprint of power plants within PJM was unchanged for this time period. As a result, the complete data set includes 52,573 hourly observations. Unless stated otherwise, the results in this section assumes that the high natural gas price regime (Regime 1) runs from 2005 through January 7, 2009 and the low natural gas price regime (Regime 2) started on January 8, 2009.

Table 1 summarizes the data for day ahead and real time wholesale electricity price and load levels. The data suggest that both day ahead and real time prices dropped significantly from the high to low natural gas price regimes. The standard deviation of prices dropped approximately proportionally with prices leaving the coefficient of variation unchanged. Within

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It added Duquense Light Co. and Dominion Virginia Power in the first half of 2005 extending the RTO south. It added First Energy in mid 2011 extending into Ohio.

This is slightly below the number of hours during the time period. Due to technical difficulties PJM failed to post price or load data for 13 hours over the time period. These hours are spread throughout the sample period although four of the missing observations come from December 31, 2010.
each time period, day ahead and real time electricity prices are nearly identical. Real time prices exceed day ahead prices by $0.74 of the course of the study period. The difference in market prices is slightly higher during the high natural gas price regime, but those differences are not statistically significant. Figure 6 shows the distribution of price differences graphically. The Figure shows that the distribution of price differences is skewed slightly to the left which is to be expected given that real time prices are unbounded to the right. Load levels are essentially unchanged between the natural gas price regimes. This is consistent with numerous studies that have shown that electricity demand has become essentially static over the study period. The fraction of electricity purchased in the day ahead market is large and fairly stable across regimes. Over the full study period 98.9% of demand was fulfilled from day ahead market.

Table 2 summarizes the distribution of real time market prices at different load levels across regimes. Load levels are defined by deciles calculated across the full sample. We estimate mean real time PJM electricity prices using a Prais-Winsten estimator to correct for autocorrelation. Taken together, these prices represent the supply curve for wholesale electricity in PJM throughout the study period. The benefits of cheap natural gas appear in the regions of the supply curve where natural gas generation comes online. For that reason, comparing real time prices provides evidence on the level of natural gas generation at different load levels. Real time prices are lower in every load decile, but the difference is increasing as load levels rise. In Regime 1, natural gas fired generation is relatively high cost and only comes on line at high demand levels. In regime 2 natural gas fired generation is cheaper producing a much flatter supply curve at high load levels. This natural gas fired generation

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9Further, in PJM virtual traders are not permitted to sell on the real time market nor are decreasing bid functions permitted in this market. As a result, it is possible that the difference in electricity prices is not perfectly symmetric around zero since arbitrage conditions may not hold between the day ahead and real time market. In any case, this paper is concerned with the purchase decisions of electricity purchasers given a set of prices conditional on inelastic demand. As a result, we leave a more detailed investigation of the price differences across the real time and day ahead markets to future research.

10The day ahead market includes bilateral deals and other long term contracts as well utilities purchasing power to fulfill short term demand.
which resided in the upper deciles of the regime 1 supply curve has now been distributed among the middle deciles of the regime 2 supply curve lowering prices throughout. This has the impact of reducing prices at very high demand levels and shifting what was the ninth decile of the regime 1 supply curve to the tenth decile of the regime 2 supply curve. Variation in prices within a load decile have dropped slightly more than proportionally suggesting that the availability of cheap natural gas has influenced both the mean and variance of electricity prices.

The empirical specification for estimating both the short run (SR) elasticity of supply and the percent of electricity purchased on the day ahead versus real time market is straightforward. We take advantage of the market structure in PJM to estimate the short run supply elasticity of electricity under high and low natural gas price regimes. The day ahead and real time markets provide prices for a homogenous good, delivered at the same time.\footnote{We ignore market power in this paper. The Federal Energy Regulatory Commission (FERC) monitors prices, production quantities and trading behavior in this market to ensure competitive behavior. If the change in natural gas prices has changed electricity generators ability of motivation to withhold production from the day ahead market to manipulate prices we cannot separate that behavior from responses to changes in natural gas prices. Our estimates will thus be inclusive of any market power effects.}

We estimate both the short run (SR) elasticity of supply and the percent of electricity purchased on the day ahead versus real time market non-parametrically over the load profile. Assuming that forecasted load is unbiased, estimating the percent of load purchased on the day ahead market is a straightforward application of the theoretical model. In order to allow estimated parameters to vary over the load profile, we define 20 quantiles- called vigintiles- of real time load in PJM and then estimate both elasticity and percent of real time load purchased on the day ahead market for each vigintile. Put another way, we estimate the SR elasticity conditional on load. This is appropriate since the SR elasticity will be a function of the generation dispatched.

Identification for both estimates takes advantage of the average cost pricing structure on the retail side of electricity markets. At every point in time demand for electricity is exogenous since retail users are not charged the marginal cost of electricity production.
Instead, total use each time period by each retail users is aggregated, total purchases by a utility are summed, and rates are set such that each user pays the percentage of that period’s total cost equal to their percentage use. As a result, the electricity purchaser on the wholesale market simply must have enough electricity in real time to meet demand or else the grid is compromised and a blackout would occur. Since wholesale electricity sales are bid in so that only the lowest cost electricity is produced, the short run elasticity of supply is identified fully off the cheapest electricity producers conditional on a level of load in the day ahead market. Similarly, the percent of electricity purchased on the day ahead market is identified off of the realized level of demand in the real time market. So long as wholesale purchasers can form an unbiased forecast of electricity of demand over the load profile, the relative size of day ahead purchases are also fully identified.

Load vigintiles are defined over the entire July 1, 2005 through June 30, 2011. This time period contains the great recession which significantly affected electricity demand. As a result, we perform difference in mean tests across regimes for each vigintile. Specifically, we estimate the following regression:

\[ Q_{RT,t} = \sum_{r=1,2} \sum_{v=1}^{20} 1\{t \in r\} 1\{Q_{RT,t} \in \text{vigintile } v\} \beta_{rv} + \epsilon_t. \]  
(3)

\( Q_{RT,t} \) represents the quantity demanded in the real time market (e.g., realized demand). The estimated \( \beta_{rv} \) coefficients are the estimated average real time load in vigintile \( v \) in regime \( r \). OLS with Newey-West error structure are used in this and all other regressions\( ^{12} \).

Figure 7 shows the estimates from equation (3) graphically. Figure 7 provides strong visual evidence that load within each quantile was roughly constant across the time periods.

\( ^{12} \)In the Newey West specifications we vary the number of lags. Because we parse the load profile into 20 bins, it is possible that a large error term will be followed by a small error term if two consecutive hours cross from one vigintile to another. For example, if at 6am load is at the upper end of the eighth vigintile then the residual is large. If at 7am load just crosses over to the bottom of the ninth vigintile the residual is small. Therefore, it is not necessarily the case that the standard 24 hour lagged error structure is the right econometric specification. Regardless the results of this and other specifications are very robust to the econometric model used in estimation. We also used Prais-Winsten as a robustness check and found identical qualitative results.
Pairwise t-tests find that the first, fourth, ninth, seventeenth and nineteenth significantly
different at the 5% level. The first, ninth and seventeenth are significantly different at the 1%
level. In each case, the difference is less than .15% of total generation within each quantile.
As a result, these differences are statistically significant but economically insignificant.

As stated above, we estimate the SR elasticity of supply within each vigintile controlling
for various fixed effects and demand from outside the PJM regime. Specifically, we use
Newey-West error lag structure to estimate the following regression:

\[
P_{RT,t} - P_{DA,t} = \sum_{r=1}^{2} \sum_{v=1}^{20} 1\{Q_{RT,t} \geq Q_{DA,t}\}1\{t \in r\}1\{Q_{RT,t} \in v\} \frac{Q_{RT,t} - Q_{DA,t}}{Q_{DA,t}} \beta_{rv} + \lambda_{my} + \gamma_{dow} + \sum_{c=1}^{7} (dd_{c,t}\gamma_{1} + dd_{c,t}\gamma_{2}) + \epsilon_{t}.
\]

(4)

\( P_{RT,t} \) and \( P_{DA,t} \) represent the real time and day ahead price for a given hour, \( t \). As a result the left hand side variable is the percent increase in price on the real time market
relative to the day ahead market. Similarly, \( Q_{RT,t} \) and \( Q_{DA,t} \) represent real time and day
ahead load. We also estimate equation (4) in levels. The coefficient of interest is again \( \beta_{rv} \).
As with the theoretical model above, we permit the short run supply elasticity to vary based
upon whether electricity production is ramped up or ramped down on the real time market:
1\{\(Q_{RT,t} \geq Q_{DA,t}\}\}. Now, \( \beta_{rv} \) the percent change in price from a one percent increase in real
time load above market clearing load in the day ahead market conditional on load being in
vigintile \( v \) and regime \( r \). Put another way, \( \beta_{rv} \) is the inverse elasticity of supply, which we
refer to as the SR elasticity. We control of month of year (\( \lambda_{my} \)) and day of week (\( \gamma_{dow} \)) fixed
effects. We also control for heating and cooling degree days in seven large cities outside of
PJM to control for exports and imports. These cities are Buffalo, New York City, Charlotte,
Cleveland, Washington DC, Indianapolis and Raleigh. This is a similar technique used to
control for electricity imports and exports in [Holland and Mansur (2008)] and [Graff-Zivin
et al. (2012)].
We estimate a similar regression to identify how the percent of load purchased on the day ahead market changes in response to low gas prices across the load profile:

\[
\frac{Q_{DA,t}}{Q_{RT,t}} = \sum_{r=1,2} \sum_{v=1}^{20} 1\{t \in r\}1\{Q_{RT,t} \in \text{vigintile } v\} \beta_{rv} + \lambda_{my} + \gamma_{dow} + \sum_{c=1}^{7} (dd_{c,t} \gamma_1 + dd_{c,t}^2 \gamma_2) + \epsilon_t. \tag{5}
\]

In equation (3) the coefficient of interest is again \( \beta_{rv} \). In this case, \( \beta_{rv} \) represents the average percent of load purchased on the day ahead market. All controls are identical to equation (4) above. The only difference is that we do not estimate equation (5) including a dummy variable for increasing or decreasing real time purchases relative to day ahead purchases. As a result, the coefficient \( \beta_{rv} \) represents the joint effect of the costs of ramping up and ramping down electricity production on purchases in the day ahead market. If the left hand side variable is equal to one, that means all electricity is purchased in the day ahead market.

Figures 8 and 9 present the results from equation (4) above in percentages and levels. We present the point estimates and 95% confidence intervals graphically both by vigintile.\(^{13}\) The top panel in each Figure corresponds to increases in production in the real time market and the bottom panel corresponds to decreases on the real time market. For example, in regime 1 for production increases, the SR elasticity actually decreases at the highest load levels. While this is unintuitive, it makes sense: as noted in the theory section above, the SR elasticity is measured as a percentage of a price change. As a result, if the day ahead market clearing price for electricity were $50 and the SR elasticity were 5%, then the real time price of electricity would be $52.50. Similarly, if the day ahead market clearing price for electricity were $100 and the SR elasticity were 5%, then the real time price of electricity would be $105. As a result the actual dollar amount of the same SR elasticity varies over the

\(^{13}\)We present a pooled estimate of elasticities (e.g., forcing the elasticity of supply to be constant for both production increases and decreases within a vigintile) in the appendix.
supply curve. As a result, at high load levels in regime one, the price of electricity is higher but the percentage increase in price which occurs from purchasing additional electricity on the real time market falls. Therefore, we also show the estimation results in levels in Figure 9. The interpretation of the y-axis coefficient in Figure 9 is a one MW increase/decrease in electricity in on the real time market relative to the day ahead quantity purchased is associated with a change in dollars given by that coefficient. The estimated pattern is qualitatively identical across both specifications.

Even more striking than within regime results is the change short run elasticities across regimes. In regime 2, the short run supply elasticity is significantly higher at high load levels in both the elasticity and the load levels specification. Put another way, the short run supply curve is significantly steeper over vigintiles 17-20 in the low natural gas price era. One likely explanation is that when natural gas prices are low in regime 2, natural gas generation is already dispatched since it is a lower price option. This is consistent with the estimates in Table 2 and Holladay and LaRiviere (2013). It could be true even of natural gas peaker units. As a result, only power plants with high ramping costs are available to meet demand on the real time market in an era of low natural gas prices.14 These results are robust to many different specifications including dropping the 2008 data from the estimation (when gas prices started to decrease and the economy entered into recession), using different Newey-West lag structures and using natural gas prices directly in the estimation process. These results are available from the authors upon request. Similarly, decreases in production on the real time market decrease the cost of electricity on the real time market by less in regime two than in regime one over vigintiles 11-16. Put another way, when there is unexpectedly low demand in vigintiles 11-16 when natural gas prices are low, real time prices fall by less. Thus, the short run supply curve is flatter for unexpectedly low demand hours over these vigintiles in regime two. This is also consistent with natural gas units providing electricity

14 The appendix has some preliminary discussion and results of examining which fuel sources are used to meet real time demand across the two regimes.
over these vigintiles as it is less costly to quickly ramp down production for these units.

Recall that the theoretical model predicts that if the elasticity of supply goes up (e.g., it is more costly to produce an additional unit of electricity on the real time market) then demand on the real time market should go down. Figure 10 displays the results from the load purchasing regression above (equation (5)). As a result, we expect that for high load levels in regime two- when elasticities are significantly higher than in regime one- we expect more electricity to be purchased in the day ahead market. Figure 10 presents the coefficient estimates for equation (5). The main prediction of the theoretical model is verified. In regime 2, when the SR elasticity is significantly higher for high demand hours, electricity purchasers buy significantly more electricity on the day ahead market. In fact, day ahead purchases are not statistically different from one in regime 2.

It may seem counterintuitive that in high demand hours in regime one electricity purchasers only buy roughly 96% of electricity on the day ahead market but recall that the price within high load quantiles in regime 1 is very high ($111/MWhr in the highest decile). As a result, the cost of having too much electricity purchased if the real time load is unexpectedly low was very large. As a result, we find some evidence that electricity purchasers are risk averse.

As a robustness check, we pool hours of increases and decreases and rerun these regressions for a different low natural gas price regime start date, choosing April 1, 2009 as the first day of regime 2. Results are shown in Figure 11. Using a later start date makes the results even more stark for the elasticity estimates. Estimated purchasing behavior displays a similar pattern as well. We take this as evidence that these results are not sensitive to the start date used for lower natural gas prices.

The estimation results do offer some additional puzzles which require additional investigation. For example, there are statistically different elasticities at the ninth decile but the percent purchased in the day ahead market is not statistically different across regimes. This is likely due to the decrease in electricity wholesale price within that quantile: wholesale
real time prices fell from roughly $53 to $38 within that quantile, a decrease of nearly 30%. It is unclear precisely how that tradeoff between a high SR elasticity but a lower wholesale price tradeoff with one another for electricity purchasers. The downward trend of day ahead purchases in regime one imply that electricity purchasers are risk averse: if electricity purchasers are risk neutral, then the level of electricity prices ($c$ in the theoretical model) should not affect the relative purchase behavior.

In sum, this subsection finds that the RTO’s flexibility to allow electricity purchasers to choose how much electricity to buy on the day ahead versus real time market is used as predicted by a simple theoretical model. When the relative cost of purchasing electricity on the real time market increases, utilities buy less on the real time market. The next subsection uses a simulation to estimate the cost savings due to allowing this flexibility.

4.3 Simulation Results

This section evaluates the benefits of the RTO’s flexibility in demand across the day ahead and real time market using simulation methods. The goal of the simulations is to show the cost savings from flexibility. As a result, we construct a counterfactual that finds the increase in cost of electricity for the year had the RTO not had the ability to shift demand between the real time and day ahead market. Put another way, we simulate the compensating variation associated with policy inflexibility.

The simulation calculates the total hourly cost of electricity in the wholesale market, then aggregates to yearly expenditures. We maintain that the day ahead and real time market occur for every hour $h$ across regimes $i = 1, 2$. Assume that $Q_h$ represents realized demand in a particular hour and that, as above, forecasted demand is unbiased but subject to some uncertainty. Since demand is inelastic in the short run, $Q_h$ is fully exogenous. Not exogenous, however, is demand for electricity on the day ahead versus the real time market. Define $Q_{d,h}(\overline{MC}_i, \xi, \hat{Q}_h)$ to be the demand function for electricity in the day ahead market.
as a function of the vector of day ahead marginal costs, $MC$. These marginal costs of production represent wholesale prices to electricity purchasers given the auction mechanism in this market. Demand is also a function of short run elasticities, $\epsilon$, and a load forecast, $\hat{Q}_h$. The demand function could also be a function of higher moments of the load forecast but we suppress inclusion of those terms for expositional simplicity. Since prices, elasticities and demand functions have all been shown to change as natural gas prices fell in early 2009, we denote regimes with superscripts so that $Q^i_{d,h}(MC^i, \epsilon^i, \hat{Q}_h)$ for $i = 1, 2$. As a result, in regime $i$, the realized total cost for electricity in an hour $h$ given realized demand of $Q_h$ is

$$
TC^i_h(Q_h) = Q^i_{d,h}(MC^i, \epsilon^i, \hat{Q}_h) * MC^i_d(Q^i_{d,h}(\cdot)) \\
+ \epsilon(Q^i_{d,h}(\cdot)) * MC^i_d(Q_{d,h}(\cdot)) * (Q_h - Q^i_{d,h}(MC^i, \epsilon^i, \hat{Q}_h)).
$$

(6)

In equation (6), $MC^i_d(Q_{d,h}(\cdot))$ represents the unit price paid for electricity by electricity purchasers as a function of the quantity of load purchased on the day ahead market, $Q^i_{d,h}(\cdot)$. As a result, total expenditures for purchases on the day ahead market are $Q^i_{d,h}(\cdot) * MC^i_d(Q_{d,h}(\cdot))$. Purchases on the real time market are subject to additional increase in cost due to the slope of the short run marginal cost curve. As a result, the price of purchasing a unit of electricity on the real time market is $\epsilon(Q^i_{d,h}(\cdot))MC^i_d(Q_{d,h}(\cdot))$ where the elasticity represents a constant percentage increase in cost over the day ahead market. Finally, the total quantity of electricity purchased on the real time market is the realized demand less what was purchased on the day ahead market.

The regulatory flexibility that is the focus of this research is allowing market participants to respond to market signals. Specifically, we are interested in how electricity purchasers alter their purchase decisions in the day ahead market as the relative price of electricity between the day ahead and real time markets change. The behavior afforded to electricity purchasers via regulatory flexibility is summarized by the function $Q^i_{d,h}(MC^i, \epsilon^i, \hat{Q}_h)$. In some regions
of the country, such as the in Texas, a regulatory body has until very recently, dictated day ahead purchases. In these markets the demand curve in the day ahead market cannot adjust to market conditions then regardless of day ahead costs and short run elasticities, the percentage of electricity purchased in the day ahead market is the same. Put another way, it would imply \( Q_{d,h}^1(\cdot) = Q_{d,h}^2(\cdot) \) even as the arguments of the demand functions change.

In order to accurately identify the benefit of regulatory flexibility in this market, we perform the following simulation: we estimate the short run elasticity, hourly load levels and day ahead load demand functions for each vigintile as before. This allows us to calculate total wholesale purchases using equation (6). We then ask how much more electricity expenditures would have been, had day ahead demand functions in regime two not been allowed to deviate from the regime one demand functions. Specifically, we calculate our counterfactual total cost as:

\[
TC^{cf}_h(Q_h) = Q_{d,h}^1(MC^1_1, \epsilon^1_1, \hat{Q}_h) \times MC^2_d(Q_{d,h}^1(\cdot)) \\
+ \epsilon(Q_{d,h}^1(\cdot)) \times MC^2_d(Q_{d,h}(\cdot)) \times (Q_h - Q_{d,h}^1(MC^1_1, \epsilon^1_1, \hat{Q}_h)).
\]

(7)

We claim that the difference between equation (7) and (6) is the cost savings due to regulatory flexibility along the dimension we consider here.

In order to perform the simulation, we estimate the same specification by regime for short run elasticity as in the previous section, but with hourly RTO load, day ahead price and percent of total real time load purchased on the real time market as the left hand side variable. These regressions give point estimates and standard errors for the average load, price and RTO purchase decisions within each load decile within PJM. Using these point estimates and standard errors, we then simulate the total cost of electricity purchases on the day ahead and the real time market for an entire simulated year (e.g., 12,410 hours) assuming normally distributed stochasticity for each hourly draw of each variable. We assume that
exactly 10% of hours are allocated to each load decile.

One intuitive way to display the results of the simulation is to calculate the percent of total costs for each hour that are incurred in the real time versus the day ahead market and compare the distributions of those percentages across regimes. Figure 7 and Figure 8 show exactly these distributions for regime 1 and regime 2 respectively. First, in both figures, there are hours in which there are negative costs associated with real time purchases. This occurs, both in the actual and simulated data, because sometimes the real time price of electricity is less than the day ahead price due to unexpectedly low demand. Second, in the first regime, there are a significantly larger proportion of costs which are incurred in the real market relative to the second regime. This is due to the relatively low level of purchases in the day ahead market in regime 1. Due to a relatively low short run elasticity in the ninth and tenth load deciles in regime 1, the RTO purchased large quantities of expensive electricity between 2005 and 2009. Conversely, in regime 2, the RTO purchased much smaller quantities of electricity on the real time market at high load levels since the short run elasticity increased.

Our main counterfactual is calculated assuming the RTO purchased quantities on the day ahead and real time markets they did in regime 1. Put another way, in our counterfactual if the RTO forecasted true load to be \( Q \sim N(\hat{Q}, \sigma^2) \), they choose \( Q_{d,h} \) such that marginal costs across the day ahead and real time markets are equal based upon the parameters in regime 1. We then take those relative day ahead and real time demand levels and calculate costs based upon prices in regime 2. As a result, our counterfactual assumes rigid demand by the RTO in the day ahead market.

Figure 8 shows the main counterfactual in this paper. Figure 8 shows the simulation of percentage of expenditures incurred in the real time market in regime 2 given the RTO chose demand levels across days by regime 1’s equilibrium condition. Figure 8 shows a much large right tail than Figure 8 as a significantly large proportion of expenditures occur in the real time market. Figure 10 lays the regime 2 simulation and the regime 2 counterfactual on top of one another (green being the counterfactual). The zero percent expenditures in
the counterfactual reflect higher costs on the extreme left tail of the distribution of regime 2 simulations.

We can also calculate the increase in total costs which the RTO would pay if the did not have this flexible policy. Performing 100 simulations, the average increase in costs due to inflexible policy across price regimes is 4.2%. In dollar terms, this amounts to $1.2 billion dollars per year in addition direct costs for wholesale electricity in PJM if the RTO did not have the flexibility given to the by FERC.

5 Conclusion

In this paper we have developed a straightforward model of the electric grid operators ability to allow electricity purchasers to fulfill demand across multiple markets in the face of uncertainty. We develop a simple theoretical model showing how electricity purchasers, when given the regulatory flexibility, will respond to a change in the short run supply elasticity of electricity. The model predicts that when the cost of buying electricity on the real time market goes up, less power should be purchased on the real time market.

We use the technological advances in extractive industries as exogenous variation for decrease in natural gas prices in the US during the late 2000s. We estimate the timing of this decrease using two diffract techniques. We then estimate how the change in natural gas prices affected the short run supply elasticity for electricity. We find that the short run elasticity of supply increased dramatically at the upper load quantiles. Intuitively, natural gas fired generators were concentrated near the top of the supply curve in times of high natural gas prices. As a result, the reduction in natural gas price had an unequal impact across the supply curve. We use this variation in exposure to natural gas fired generation across quantity quantiles to identify the impact of cheap natural gas for electricity purchasers like utilities. We find that purchasers used regulatory flexibility afforded them by the the RTO and FERC as predicted by the model to save roughly $1.2 billion dollars per year on the
wholesale market. These results show that not only in regulatory flexibility desirable in some cases, but that economic reforms may still be the most cost effective way to alter electricity consumption patterns, and consumption patterns more generally, in OECD countries.

There are several extensions which need to be performed. First, more work is needed to control for seasonality in the Markov Switching Model. Second, it is not clear what the proper counterfactual is in the simulation exercise. Perhaps always purchasing a constant percent of forecasted load in the day ahead market is a better comparison for gaging total savings from this regulatory flexibility. Third, work is need to identify the effect of the change in the composition of electricity purchases across the day ahead and real time markets on emissions over this time frame. Fourth, additional work is needed to parse out the importance of the level effect of wholesale electricity price changes on day ahead versus real time purchases.
References


Tables and Figures

Figure 2: Natural gas prices

Note: Natural gas prices for one month future contracts from 1994-2012 in dollars per million BTU’s. Data source: Energy Information Administration.
Note: Number of natural gas well production days in Pennsylvania from 2000-2010. A roughly 33% increase occurs and persists in 2008. Graph represents raw natural gas production not weighted by total volume.
Figure 4

Note: Markov Switching Model estimation of regime switch. The high state is indexed by one and the low state by two. Top panel shows the price data for Henry Hub spot prices. The second panel shows the standard deviation in the system conditional on the estimated state. The third panel shows the probability of being in each regime. Note that $t=1000$ is January 6, 2009.
Note: Results rolling Chow Tests to identify structural break in first differenced natural gas spot market prices. Data is NY Mercantile Exchange spot market commodity prices provided by Bloomberg. Break with largest magnitude occurs between March and April 2009. Later breaks are positive signifying the small rebound of natural gas prices shown in Figure 1.
Table 1: Electricity Market Summary Statistics by Regime

<table>
<thead>
<tr>
<th>Variable</th>
<th>Regime 1</th>
<th>Regime 2</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA Price</td>
<td>56.17</td>
<td>40.83</td>
<td>50.14</td>
</tr>
<tr>
<td></td>
<td>(27.61)</td>
<td>(18.12)</td>
<td>(25.46)</td>
</tr>
<tr>
<td>RT Price</td>
<td>57.23</td>
<td>41.08</td>
<td>50.88</td>
</tr>
<tr>
<td></td>
<td>(35.46)</td>
<td>(25.05)</td>
<td>(32.74)</td>
</tr>
<tr>
<td>DA Load</td>
<td>79888.4</td>
<td>79741.6</td>
<td>79830.7</td>
</tr>
<tr>
<td></td>
<td>(14277.5)</td>
<td>(16608.5)</td>
<td>(15236.5)</td>
</tr>
<tr>
<td>RT Load</td>
<td>80468.6</td>
<td>81015.7</td>
<td>80683.7</td>
</tr>
<tr>
<td></td>
<td>(14902.1)</td>
<td>(15891.7)</td>
<td>(15300.9)</td>
</tr>
</tbody>
</table>

Note: Hourly day ahead demand, actual (real time) demand, day ahead price and real time price for each hour from July 1, 2005 through June 30, 2011. High natural gas price regime (Regime 1) runs from 2005 through January 7, 2009 and the low natural gas price regime (Regime 2) started on January 8, 2009. $n = 52,573$
Table 2: Real time electricity prices in PJM

<table>
<thead>
<tr>
<th>Load Decile</th>
<th>Regime 1</th>
<th>Regime 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>24.58</td>
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<tr>
<td></td>
<td>(10.20)</td>
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<td>2</td>
<td>33.44</td>
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<td></td>
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<tr>
<td>3</td>
<td>40.63</td>
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<tr>
<td></td>
<td>(17.75)</td>
<td>(8.16)</td>
</tr>
<tr>
<td>4</td>
<td>46.24</td>
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<td></td>
<td>(20.18)</td>
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<td>(25.26)</td>
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<tr>
<td></td>
<td>(50.73)</td>
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<td>Total</td>
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<td>41.08</td>
</tr>
<tr>
<td></td>
<td>(35.46)</td>
<td>(25.05)</td>
</tr>
</tbody>
</table>

Note: Average hourly real time electricity prices ($/MWHR) for PJM wholesale market by natural gas price regime and load decile. Standard deviation of price within a regime-load decile bin in parentheses. Hourly day ahead demand, actual (real time) demand, day ahead price and real time price for each hour from July 1, 2005 through June 30, 2011. High natural gas price regime (Regime 1) runs from 2005 through January 7, 2009 and the low natural gas price regime (Regime 2) started on January 8, 2009. n = 52,573. Robust Prais-Winsten estimation used.
Note: Distribution of price differences \((P_{rt} - P_{da})\) between real time and day ahead prices over the entire sample period. The distribution is slightly skewed to the right which is expected given that real time prices are unbounded. The price differences are centered around zero.
Figure 7

Note: Real time load level by vigintiles (20 quantiles) across regimes. Robust standard errors implemented and \( n = 52,573 \). Pairwise t-tests find that the first, fourth, ninth, seventeenth and nineteenth significantly different at the 5% level. The first, ninth and seventeenth are significantly different at the 1% level. In each case, the difference is less than .15% of total generation within each quantile.
Note: Short Run Elasticity by vigintiles (20 quantiles) across regimes. Top panel shows days in which there were positive purchases on the real time market. Bottom panel shows days in which there were negative purchases on the real time market. Load deciles defined over entire dataset (July 2005- June 2011). Both panel shows estimates by vigintile. Newey-West error lag structure used and 95% confidence intervals shown as error bands. Regime 1 runs from July 2005- Jan 7, 2009 and regime 2 runs from Jan 8, 2009 through June 2011. $n = 52,573$
Figure 9

*Note:* Level change in price due to a one MegaWatt increase in electricity purchased on the real time market by vigintiles (20 quantiles) across regimes. Top panel shows days in which there were postive purchases on the real time market. Bottom panel shows days in which there were negative purchases on the real time market. Load deciles defined over entire dataset (July 2005- June 2011). Both panel shows estimates by vigintile. Newey-West error lag structure used and 95% confidence intervals shown as error bands. Regime 1 runs from July 2005- Jan 7, 2009 and regime 2 runs from Jan 8, 2009 through June 2011. n = 52,573.
Note: Load Ratio ($\frac{Q_{DA}}{Q_{RT}}$) by vigintiles (20 quantiles) across regimes. Load deciles defined over entire dataset (July 2005- June 2011). Top panel shows estimates by vigintile, bottom panel shows estimates by mean generation level of each vigintile. Newey-West error lag structure used and 95% confidence intervals shown as error bands. Regime 1 runs from July 2005- Jan 7, 2009 and regime 2 runs from Jan 8, 2009 through June 2011. n = 52,573
Note: Short Run Elasticity and Load Ratio (\(\frac{Q_{DA}}{Q_{RT}}\)) by vigintiles (20 quantiles) across regimes. Load deciles defined over entire dataset (July 2005- June 2011). Newey-West error lag structure used and 95% confidence intervals shown as error bands. Regime 1 runs from July 1, 2005- March 31, 2009 and regime 2 runs from April 1, 2009 through June 30, 2011. \(n = 52,573\)
Figure 12

Regime 1

Note: Simulated percentages of total wholesale electricity costs for an entire year parameterized using July 1, 2005- Jan 7, 2009 data. All uncertainty assumed orthogonal.
Figure 13

Note: Simulated percentages of total wholesale electricity costs for an entire year parameterized using Jan 8, 2009-June 30, 2011 data. All uncertainty assumed orthogonal.
Figure 14

Note: Simulated percentages of total wholesale electricity costs for an entire year parameterized using elasticity estimates from Jan 8, 2009-June 30, 2011 data but quantity demanded estimates from July 1, 2005-Jan 7, 2009 data. Image shows the distribution of costs had RTO not had flexibility to adjust demand levels.
Figure 15

Note: Simulated percentages of total wholesale electricity costs for an entire year parameterized using elasticity estimates from April 2009-June 2011 data but quantity demanded estimates from July 2005-March 2009 data in green. Simulated percentages of total wholesale electricity costs for an entire year parameterized using April 2009-June 2011 data in blue. Image shows the distribution of costs had RTO not had flexibility to adjust demand levels across the day ahead and real time markets.
6 Appendix

The pooled elasticity estimates from equation (4) are shown in the figure below:
Figure 16

Note: Short Run Elasticity by vigintiles (20 quantiles) across regimes. Load deciles defined over entire dataset (July 2005- June 2011). Top panel shows estimates by vigintile, bottom panel shows estimates by mean generation level of each vigintile. Newey-West error lag structure used and 95% confidence intervals shown as error bands. Regime 1 runs from July 2005- Jan 7, 2009 and regime 2 runs from Jan 8, 2009 through June 2011. n = 52,573
A further conclusion of the model is that for any load levels for which the real time supply curve shifts down, observed forecast errors of the RTO will decrease as they begin to purchase less electricity on the day ahead market. We rearrange the previous regression to study that forecast error directly:

$$\text{ForecastError}_h = \beta_i \text{LoadDiff}_h \ast \text{Regime}_i \text{LoadDecile}_h + \lambda_{my} + \gamma_{dow} + \epsilon_h$$  \hspace{1cm} (8)$$  

where ForecastError$_h$ is simply measured as the hourly real time load minus the hourly day ahead load transacted the previous day. Figure 17 summarizes these results. During regime 1 in hours where demand is in the first decile forecast errors tend to be very small, but they increase monotonically across deciles. The situation is reversed in regime 2. Forecast errors are relatively large at low demand levels, but decrease with across load deciles. At high demand levels, where we observe a statistically significant shift in the supply curve we also observe statistically significant decreases in forecast error as predicted by the model.
Note: Forecast error by load decile and natural gas price regime. Forecast error is defined as the difference between the quantity in the real time market minus demand from the day ahead market. Regime 1 is defined as July 2005- March 31, 2009. Regime 2 is defined as April 1, 2009- June 2011.