

Electricity Market Price Volatility: The Importance of Ramping Costs

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February 6, 2014

Abstract

Although electricity market price behavior generally has been well studied in the last decade, the literature is sparse when discussing the importance of generator ramping costs to price volatility. This paper contributes to the literature by first formalizing the intuitive link between ramping costs and price volatility in a multi-period competitive equilibrium. The fundamental result of the model shows how price volatility rises with ramping costs. This notion is tested empirically using a two-stage least squares (2SLS) regression to correct for endogeneity issues between generator capacity and price behavior. The econometric results confirm that price volatility is significantly decreased by additional natural gas capacity, which has comparatively low ramping costs. These results are robust to a pooled event study analysis, as well as a generalized autoregressive conditional heteroskedasticity (GARCH) model. This marks the first rigorous study to quantify the externalities to price behavior within the New England market's generating profile, showing several million dollars worth of price stability provided per year by each new natural gas generator.

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1 Introduction

Within the past fifteen years, most electricity markets across the United States have restructured to allow competition in the generation of electricity. Electricity price behavior has been extensively studied as it relates to market design (Wolak and Patrick, 2001, Borenstein et al., 2002, Chang and Park, 2007, Metaxoglou and Smith, 2007, Bushnell et al., 2008, Bask and Widerberg, 2009) and price volatility generally (Hadsell et al., 2004, Worthington et al., 2005, Zareipour et al., 2007, Higgs and Worthington, 2008, Higgs, 2009). However, there are fewer studies which examine how price volatility is influenced by the generating profile of the market. This is important because high volatility has plagued wholesale electricity prices since restructuring, creating major implications for risk-averse market participants and system operators tasked with grid reliability. Further, price volatility is a primary input into conventional options pricing models, pushing real costs onto consumers of electricity as power purchasing retailers use costly options to hedge away from price risk. When compared to other energy commodities, intra-day volatility in wholesale electricity markets is many times larger and varies across regions. For example, daily electricity market volatility ranges from 6-28% compared to 1-1.5%, 2-3%, and 3-5% for stock indices, crude oil, and natural gas, respectively (Simonsen, 2005, Zareipour et al., 2007).

Much of this variability is driven by the physical characteristics of electricity, notably the requirement to perfectly adjust supply to meet a demand that varies significantly throughout the day and across seasons. The mainstream view is that high price volatility within electricity markets is due to the lack of hourly retail pricing in combination with the lack of cost-effective electricity storage mechanisms. In traditional commodity markets, forward contracts stabilize spot prices because any deviations allow for arbitrage through selling previously stored goods (Kaldor, 1939, Working, 1948). However, current technologies do not allow cost-effective electricity storage on any meaningful scale, rendering traditional forward pricing models inapplicable. Instead, Bessembinder and Lemmon (2002) develop a seminal equilibrium model of forward contracts between risk-averse electricity generators and retailers, which implies a forward contract premium to accompany high expected demand or demand variance. The essentials of their model are empirically supported (Longstaff and Wang, 2004, Cartea and Villaplana, 2008, Douglas and Popova, 2008), though more recently Haugom and Ullrich (2012*b*) find that the forward price has converged to an unbiased predictor of the spot price.

While Bessembinder and Lemmon (2002) capture the essentials behind forward contracts in non-storable commodities, their model ignores the storability of inputs to electricity generation. Intuitively, if inputs can be stored and capacity exists to instantaneously convert these inputs into electricity, then a stabilizing pressure is applied to price in the event of demand shocks. Further, there exists a cross-commodity price relationship as pointed out by Routledge et al. (2001) in an extension of their previous

work (Routledge et al., 2000). This notion is empirically tested by Douglas and Popova (2008), who find that larger natural gas storage decreases the premium of forward contracts. While they note that the effectiveness of the indirect physical hedge requires availability of transmission and generation capacity, this is notably absent from their empirical specification. Further, natural gas storage is likely endogenous to electricity price and forward contract premiums, creating bias in their empirical estimates. In a separate analysis across European electricity markets, Huisman and Kilic (2012) attribute differences in risk premiums to be from differences in the storability implicit within the generation profile, a point more explicitly noted previously (Huisman and Kilic, 2010). However, cross-sectional analysis is inadequate to infer causal relationships when the markets also vary widely in both observable and unobservable characteristics.

Intuitively, different generator technologies would affect volatility differently, as they vary in their ability to adjust output. Heterogeneity in ramping costs, or costs of adjusting output, allow some generators to flexibly adjust output during periods of higher demand, putting more downward pressure on prices compared to other generators. In this paper, I seek to understand the role of ramping costs in the price volatility of non-storable and perishable commodities. More specifically, I ask three connected research questions related to natural gas capacity, which has comparatively low ramping costs (Wolak, 2007, Reguant, 2014). First, what is the impact of additional natural gas capacity on electricity price stability and how does this compare to inflexible capacity such as nuclear? Further, what is the value of such volatility reductions to power purchasers? Lastly, how does the forward premium change on price contracts in the presence of additional natural gas capacity?

To explore this topic, a basic theoretical framework is developed to establish the connection between price volatility and generator ramping costs. Under standard economic assumptions, the analytical model clearly suggests that price volatility increases with generator ramping costs. Further, the theoretical model implies a reduced form econometric specification where the intra-day price volatility is a function of natural gas capacity, intra-day demand volatility, daily average demand, and unobservable time trends. To explore these ideas empirically, I use high-frequency price data from the New England Independent Systems Operator for the period 2005-2011. Data on natural gas capacity and nuclear capacity outages are taken from the U.S. Energy Information Agency and the U.S. Nuclear Regulatory Commission, respectively. The task is complicated by endogeneity between price and capacity, since natural gas is the marginal generator in New England. To correct for the endogeneity from this simultaneity, I use a two-stage least squares econometric specification and find strong evidence that natural gas capacity additions reduce price volatility an order of magnitude more than additional nuclear generation capacity. These results are robust to a pooled event study analysis, as well as a generalized autoregressive conditional heteroskedasticity (GARCH) model. I attribute the differences in volatility reductions to the low ramping

costs of natural gas, which provide benefits to price stability worth several million dollars per generator per year.

This research adds to the broad existing literature from economics and finance that discusses electricity market design, electricity price behavior, and forward premiums on perishable commodities. By formalizing the link between ramping costs and price volatility, the model provides a clear theoretical mechanism to explain how ramping costs increase price volatility. Most importantly, this research provides the first rigorous empirical analysis that supports the role of natural gas capacity to reduce price volatility. Lastly, this research provides concrete evidence for policymakers to consider the pecuniary externalities associated with generation types, underscoring the importance of investments into ramping ability. While environmental externalities are beyond the scope of this analysis, ramping costs are important for such researchers to consider because they fundamentally alter the abatement cost curves.

The remainder of this paper proceeds as follows. Section 2 gives a brief background of the New England electricity market structure while Section 2.1 discusses ramping costs in more detail. The theoretical framework is established in Section 3, which formalizes the intuitions described above into a basic analytical model. The econometric strategy to test these relationships is described in Section 4, while the related data are discussed in Section 5. The results are presented in Section 6, with the option pricing effects noted in Section 6.1. Finally, additional regression analysis studying the impact of natural gas capacity on the forward premium is provided in Section 7, while Section 8 concludes.

2 New England ISO Market Background

Prior to the 1990s, New England's electricity market was comprised of vertically integrated monopolies that were heavily regulated. Private and municipal utilities managed the region's electricity grid through the New England Power Pool (NEPOOL) created in the early 1970s. However, by 1996 the Federal Energy Regulatory Commission (FERC) issued orders that encouraged wholesale electricity markets for competitive electricity generation. The FERC created general guidelines with a recommended market structure where a non-profit Regional Transmission Organization (RTO) is entrusted to manage the transmission grid and electricity markets. This paved the way for the creation of the Independent Systems Operator of New England (ISO-NE) in 1997 to oversee the market restructuring, ensure grid reliability, and establish competitive markets. (ISO-NE, 2014*a*)

New England's competitive electricity markets were first implemented in 1999 and now cover 14 million people across six states.¹ The wholesale market includes over 500 participants and the ISO-NE coordinates over 8,000 miles of transmission lines (ISO-NE, 2014*c*). After restructuring, consumers can

¹The New England market includes Maine, Vermont, New Hampshire, Massachusetts, Connecticut, and Rhode Island.

choose between four licensed utilities which are responsible for the retail delivery of electricity. Typically the consumers pay a constant marginal cost for electricity at a rate fixed for several months and face no hourly price pressure from the wholesale market. Thus, consistent with the prior literature, the rest of this analysis assumes demand to be exogenous to wholesale prices at the hourly level.²

Major changes to the wholesale market occurred in 2003 when the ISO-NE adopted the “Standard Market Design” of FERC, which established locational marginal pricing³, financial transmission rights⁴, and a dual-settlement market. The dual-settlement market system provides a day-ahead market and a real-time market, which clear separately through two competitive auctions. (ISO-NE, 2014*b*)

In the day-ahead market, participants provide hourly bids for the supply and demand⁵ of electricity that will be dispatched the following day. For each hour of scheduled delivery, the bids are due by noon of the prior day. ISO-NE then stacks the bids into hourly aggregate supply and demand curves and schedules electricity to be delivered for all bidders below the intersection of supply and demand. While the day-ahead market is purely financial since no electricity is physically delivered, suppliers must deliver the agreed amount of electricity in the corresponding hour of the following day. In the event of equipment malfunction, for example, the supplier cannot deliver the ex-ante scheduled amount of power and they are required to buy the appropriate amount in the real-time market. (ISO-NE, 2014*b*)

After the first round of commitment in the day-ahead market, ISO-NE performs a reliability assessment based on its own demand forecast and a “re-offer” period begins. Supply and demand that has not been previously scheduled is eligible for bidding in this market, which forms the foundation of the real-time market. Throughout the following trading day the ISO-NE physically balances supply and demand through these hourly bids while maintaining grid stability through a sufficient operating reserve of electricity. The real-time market prices are from ex-post settlements based on actual power delivery that may deviate from expected demand. (ISO-NE, 2014*b*)

Although the day-ahead market is purely financial, risk averse market participants may prefer the day-ahead schedule. The day-ahead pricing is typically more stable because it is based on expected outcomes, but real demand variations can be unexpected. To ensure the convergence of day-ahead prices

²At longer time horizons, changes in wholesale electricity prices are eventually passed on to the consumer but the exogeneity assumption is arguably most appropriate for the frequency of the data used in this analysis.

³Locational marginal pricing (LMP) is required for efficient markets because of transmission capacity constraints which impose congestion costs. For each node and load zone in the ISO-NE, supply and demand offers are submitted such that the LMP provides the competitive price inclusive of congestion costs. If congestion and transmission losses are zero, the efficient price is equivalent across all nodes and their zonal aggregates.

⁴Since LMP includes congestion costs paid to the ISO-NE by power purchasers, the suppliers may receive less revenue than the final price that includes congestion costs. Thus, financial transmission rights (FTR) are auctioned to market participants, giving them a share of the real-time congestion payments that are absent from the day-ahead market price. For power purchasers, this acts as a hedge against unexpected higher congestion costs, while it can also provide additional revenue for generators or speculators.

⁵While demand is exogenously determined by retail customers, retail utilities have a choice to buy electricity in the day-ahead market or the real-time market. Any unscheduled electricity demanded in the day-ahead market is required to be purchased in the real-time market.

with real-time prices, the ISO-NE also allows “virtual bids”, which are purely financial trades in the day-ahead market that must be closed out in the real-time market. Thus, any consistent and profitable arbitrage opportunities between the two markets should be removed in the presence of virtual bidding, leaving only a small risk premium.

Overall, the New England market is primarily served by electricity generation from nuclear and natural gas. The total GWh generation by source is provided by the ISO-NE and shown in Table 1 for 2005-2011, the entire period studied in this analysis. In 2011, generation from nuclear and natural gas facilities comprised around 67% of total generation, not including the 13% from dual-fuel generators, much of which can be attributed to natural gas as well. Meanwhile, coal, hydro, and aggregate non-hydro renewables⁶ each generate close to 6% of the ISO-NE total. Thus, this analysis focuses on the two largest generator types of nuclear and natural gas to understand the role of ramping costs in price volatility. Generally, natural gas generators are the marginal unit throughout most of the year.

Table 1: New England Generation Profile: Annual GWh from 2005-2011

Source	2011	2010	2009	2008	2007	2006	2005
Total Generation	120,610	126,416	119,437	124,749	130,723	128,050	131,877
	100%	100%	100%	100%	100%	100%	100%
Gas	46,378	42,042	38,163	38,338	39,367	39,425	38,583
	38.45%	33.26%	31.95%	30.73%	30.11%	30.79%	29.26%
Nuclear	34,283	38,364	36,231	35,547	36,972	36,923	34,609
	28.42%	30.35%	30.33%	28.49%	28.28%	28.83%	26.24%
Oil/Gas [†]	15,925	15,542	12,487	12,721	15,791	13,542	16,567
	13.2%	12.29%	10.45%	10.2%	12.08%	10.58%	12.56%
Hydro	8,252	7,227	8,354	8,466	6,385	7,498	6,739
	6.84%	5.72%	6.99%	6.79%	4.88%	5.86%	5.11%
Renewables	7,261	7,686	7,331	7,539	7,818	7,675	7,599
	6.02%	6.08%	6.14%	6.04%	5.98%	5.99%	5.76%
Coal	7,080	14,131	14,558	18,596	19,770	19,375	20,789
	5.87%	11.18%	12.19%	14.91%	15.12%	15.13%	15.76%
Pumped Hydro	1,149	854	1,419	1,623	1,744	1,582	1,339
	0.95%	0.68%	1.19%	1.3%	1.33%	1.24%	1.02%
Oil	282	570	895	1,918	2,877	2,030	5,652
	0.23%	0.45%	0.75%	1.54%	2.2%	1.59%	4.29%

[†] ISO-NE does not have data splitting generation by fuel in dual-fuel units

While the ISO-NE wholesale electricity market generally operates independently, there is also thirteen interconnections that allow for the purchase and sale of electricity to grids in New York and Canada. The annual flows of electricity from 2005-2011 are listed for the ISO-NE in Table 2. On average, net imports account for 5.7% of electricity consumed within the ISO-NE. The ISO-NE is a net exporter of electricity to the New York ISO, but a net importer from Quebec. From 2005 to 2011, demand has decreased by

⁶Within non-hydro renewable generation for 2011, 4.9% of total generation is from wood and refuse, 0.6% from wind, and less than 0.3% from landfill gas or solar.

Table 2: New England Electricity Flow: Annual GWh from 2005-2011

	2011	2010	2009	2008	2007	2006	2005
Total Demand	129,163 100%	130,773 100%	126,838 100%	131,753 100%	134,466 100%	132,087 100%	136,355 100%
Total Generation	120,610 93.38%	126,416 96.67%	119,437 94.16%	124,749 94.68%	130,723 97.22%	128,050 96.94%	131,877 96.72%
Pumped Hydro [†]	-1,589 -1.23%	-1,183 -0.9%	-1,963 -1.55%	-2,247 -1.71%	-2,403 -1.79%	-2,156 -1.63%	-1,819 -1.33%
Imports	15,880	12,781	15,226	14,256	12,269	10,762	10,152
Exports	5,738	7,242	5,863	5,005	6,122	4,569	3,855
Net Imports	10,142 7.85%	5,539 4.24%	9,363 7.38%	9,251 7.02%	6,146 4.57%	6,193 4.69%	6,297 4.62%

[†] Pumped hydro is a net loss of energy generation but can still occasionally be optimal. Essentially it provides relatively small indirect storage of electricity during low demand periods that is released during peak demand periods

5.3% while total generation has decreased by 8.5%. The difference is made up though additional imports which have generally increased over time.

2.1 Ramping Costs

Electricity generation is itself a complex process, made more complicated through the necessity of balancing supply and demand instantaneously to prevent grid failure. In typical fossil-fuel generators, fuel is burned to convert the embedded chemical energy into thermal energy which heats up water into steam. The pressurized steam flows to turn a turbine, which is connected to a generator that converts the mechanical energy into electricity. Nuclear reactors work in a similar way, except the nuclear reaction creates the heat for the steam turbine.

The mechanical complexity inherent to the generation process imposes extra costs to adjusting electrical output from hour to hour, known as ramping costs. Ramping costs appear through fixed investments as well as marginal costs. Within the fixed costs, physical ramping constraints accompany certain technologies and these require higher investments to overcome. For example, the turbine system and related components require special designs and construction materials to be able to rapidly ramp output and to withstand the extra stress of ramping without failure (Tanaka, 2006).

Regarding marginal costs, previous literature notes that ramping output up or down will decrease the fuel efficiency of the unit compared to a constant operating output. Further, ramping output puts additional stress on the generator components, leading to larger replacement costs. More specifically, ramping induces rapid pressurization and decompression which stresses essential pieces such as the rotor, turbine shaft blades, boiler, and turbine chamber (Tanaka, 2006). This thermal stress induces microscopic fractures known in the engineering literature as “fatigue damage”, which is the second leading cause of boiler tube failure (EPRI, 2006).

Engineering studies also note that fatigue damage to the rotor assembly increases non-linearly with ramping speed and can alter the optimal commitment of generating units (Wang and Shahidehpour, 1994, 1995). Regarding the efficient dispatch of generators, Shrestha et al. (2004) note that ramping may be used strategically in deregulated markets. They point out that, in general, generators start up and shut down slowly to avoid any ramping costs and turbine damage. However, during periods of high prices it can be profitable to incur ramping costs if the generator has sufficient capacity. This is consistent with the intuition behind the theoretical and empirical approach in Sections 3 and 4, respectively.

There are also indirect costs associated with ramping ability. Notably, if sufficient capacity does not exist with ramping capabilities to accompany demand changes then there is a large risk of system blackouts. These considerations are discussed by Chao (1983), as blackout risk imposes significant economic costs. However, my analysis is concerned primarily with price risk, so changes to the probability of grid failure due to ramping ability is left for future researchers.

Since the focus of this analysis is on natural gas capacity and nuclear capacity, it is worth noting their differences in ramping ability. The marginal operating costs of nuclear generators are estimated to be one fourth of natural gas generator marginal costs (EIA, 2013) so they generally provide the base load of the electricity supply. Further, technical constraints make cost-effective hourly ramping of nuclear generators infeasible. Nuclear generators may take an entire day to start up or shut down during planned outages, although in emergency situations the reactor can shut down very quickly. Meanwhile, natural gas generators are considered more flexible and follow increases in demand throughout the day. This is confirmed by previous literature which finds that natural gas generators have ramping costs an order of magnitude lower than coal (Wolak, 2007, Reguant, 2014). Lastly, wind and solar generators are non-dispatchable technologies without ramping options, and they are ignored in this analysis because they represent an insignificant portion of supply in the ISO-NE. However, their growing presence increases the relevance of the issues studied here because their inherent supply intermittency increases the volatility of residual demand satisfied by dispatchable generators such as natural gas.

3 Theoretical Model

Before discussing the empirical approach, this section formalizes the economic intuition into a basic dynamic model where firms generate electricity to maximize daily profits, π , in a competitive wholesale market. Each day a representative firm i chooses the optimal quantity of electricity, q , to produce in hour h , in order to maximize their profits. Assuming a competitive wholesale market, firms are given hourly market clearing electricity prices, p_h . The model uses a simple generalized cost structure similar to the previous literature (Wolak, 2007, Reguant, 2014), and assumes a convex production cost function,

$C_i(q_h)$. There is also assumed to be convexities in the ramping cost function, $R_i(\Delta_{i,h})$ where the change in hourly production is denoted as $\Delta_{i,h} = |q_{i,h} - q_{i,h-1}|$. Demand, D , is exogenous because consumers face a regulated retail price that prevents hourly price pressure, as discussed in Section 2. Adding fixed costs, F , yields the following objective function for production firms:

$$\max_{q_{h,i}} \pi_i = \sum_{h=1}^{24} \delta_h [p_h q_{i,h} - C_i(q_{i,h}) - R_i(\Delta_{i,h})] - F_i \text{ subject to } \pi \geq 0, q_h \geq 0, D_h = \sum_i^n q_{i,h} \quad (1)$$

where δ_h is the hourly market discount factor and n is the number of firms. The first two constraints represent non-negative production and non-negative daily profits, though hourly profits can be negative. The final constraint is the standard market clearing condition where production equals demand. Solving for the first order conditions yields the standard result of price equal to marginal costs, for each firm i in hour h :

$$p_h = \frac{\partial C_i}{\partial q_{i,h}} + \frac{\partial R_i}{\partial \Delta_{i,h}} \frac{\partial \Delta_{i,h}}{\partial q_{i,h}} \quad (2)$$

Recall that the intra-day variance of p on day t , denoted by σ_t^p , is defined:

$$\sigma_t^p = \frac{1}{24} \sum_{h=1}^{24} (p_{t,h} - \bar{p}_t)^2 \quad (3)$$

where \bar{p}_t is the daily average price. Substituting in equation (2) to equation (3) and simplifying yields the fundamental result of this model:

$$\sigma_t^p = \frac{1}{24} \sum_{h=1}^{24} \left(\frac{\partial C_i}{\partial q_{i,h}} + \frac{\partial R_i}{\partial \Delta_{i,h}} \frac{\partial \Delta_{i,h}}{\partial q_{i,h}} - \frac{\sum_{j=1}^{24} \left(\frac{\partial C_i}{\partial q_{i,j}} + \frac{\partial R_i}{\partial \Delta_{i,j}} \frac{\partial \Delta_{i,j}}{\partial q_{i,j}} \right)}{24} \right)^2 \quad (4)$$

As is clear from equation (4) above, price variance depends on the marginal costs of production, marginal costs of ramping, and the variance of demand. The intuition behind this result is straightforward, as the intra-day price variance will depend on the convexity of the supply curve and ramping costs. Decreasing marginal costs flattens the convexity of the supply curve where it intersects demand, which will lower the variance of price. Since the point of convexity along the supply curve is dependent on demand, the model also implies a higher variance during periods of higher demand, *ceteris paribus*.

To illustrate this point more clearly, consider a basic two period model where demand increases from D_1 to D_2 such that $\Delta = q_2 - q_1 > 0$ is the change in production. This is shown graphically on Figure 1. Without ramping costs the supply curve in both periods remains the same, shown as S , and the simple shift from D_1 to D_2 yields the prices equal to marginal production costs, $p_1 = \partial C_1$ and $p_2 = \partial C_2$

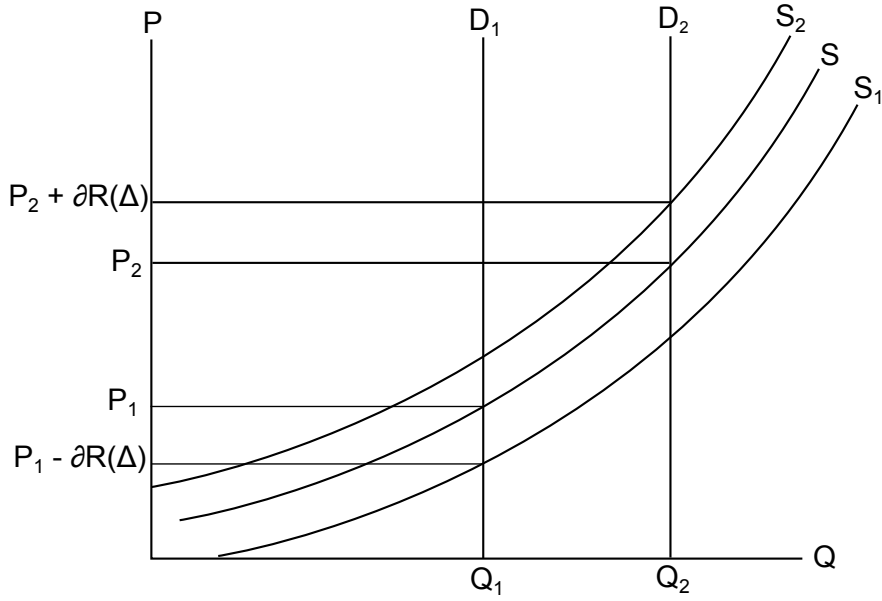


Figure 1: Supply and Demand Curves with Ramping Costs

for periods 1 and 2, respectively. However, with ramping costs, the equilibrium prices now become $p_1 = \partial C_1 - \partial R$ and $p_2 = \partial C_2 + \partial R$ for periods 1 and 2, respectively. Intuitively, firms are willing to produce quantities above those at marginal production cost in period 1 in order to have lower ramping costs in period 2. This is shown on Figure 1 as a shift from S to S_1 causing a decrease in prices.

In period 2 firms produce quantities below marginal production costs because of ramping constraints. This shifts the supply curve to S_2 in Figure 1, increasing prices beyond the equilibrium level without ramping costs. Thus, any losses from “over-production” in period 1 are recouped through lower ramping costs in the profit maximizing multi-period equilibrium.

Adding new capacity with lower ramping costs has two effects. First, the supply curve shifts outward, which will decrease the difference between p_1 and p_2 because the respective demands now intersect a flatter part of the supply curve. Second, the lower ramping costs squeezes S_1 and S_2 closer to each other, which again decreases the price difference between periods. This is shown graphically in Figure 2, where the new equilibrium is shown in red, and the old equilibrium from Figure 1 is left in light gray for comparison. Thus, the variance in prices unambiguously decreases from adding new capacity with lower ramping costs and lower marginal production costs.

As discussed in the previous sections, natural gas occupies a critical point along the supply curve where it is the marginal generating unit. Thus, there are two effects from adding new natural gas capacity as captured by the model. First, adding additional new natural gas capacity will lower total marginal costs because the new technologies are assumed to be slightly more efficient than current marginal units.

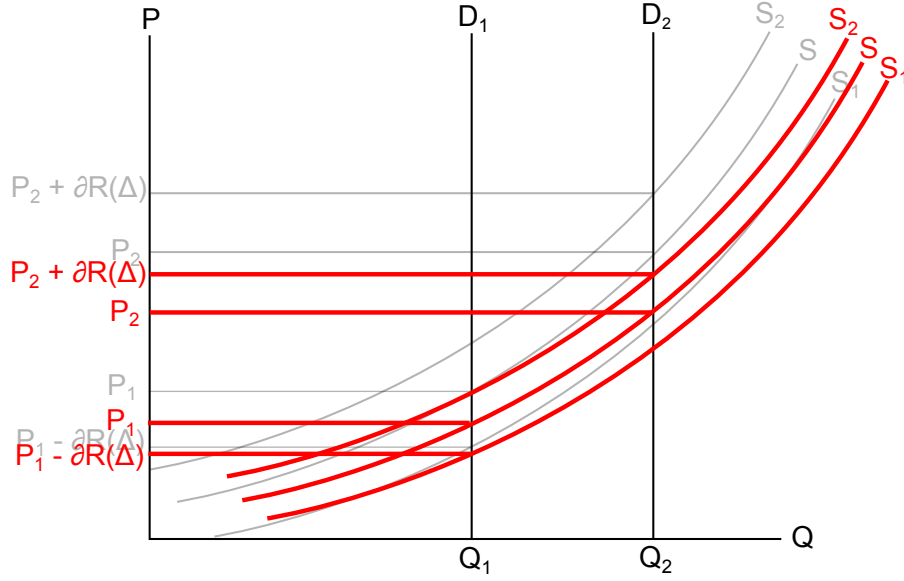


Figure 2: Shifting Supply with New Capacity

This assumption is validated empirically by the decreasing average heat-rate in natural gas units over the last decade (EIA, 2013). The second effect from adding new natural gas capacity, as captured by the model, is decreasing ramping costs. Again, this assumption is justified by empirical analysis (Wolak, 2007, Reguant, 2014), as natural gas units have lower ramping costs than coal-fired power plants. Thus, adding natural gas capacity should unambiguously decrease price volatility, *ceteris paribus*. This fundamental result of the model is tested in Section 4, and explains how production flexibility stabilizes non-storable commodity prices similar to how storage ability stabilizes traditional commodity prices.⁷

4 Econometric Specification

To test the implications and conclusion from the theoretical model in Section 3, I take advantage of high-frequency wholesale electricity price data at the hourly level. Hourly data are collapsed into daily observations which include intra-day price volatility, intra-day demand volatility, and daily average demand. The theoretical model from Section 3 implies a reduced form econometric specification where the intra-day price volatility is a function of natural gas capacity, intra-day demand volatility, daily average demand, and unobservable time trends. Thus, the model is:

$$v_t = \beta_0 + \beta_1 NGC_t + \beta_2 S_t + \beta_3 D_t + \beta_4 T_t + \varepsilon_t \quad (5)$$

⁷In storable commodity markets, production can remain constant at the average demand, since excess supply can be stored and sold in a later period. This means that ramping costs can be pushed to zero, stabilizing the prices at their marginal production costs.

where v_t is the intra-day price volatility (as measured through intra-day standard deviation) on day t , NGC_t is total natural gas capacity, S_t is intra-day demand volatility, D_t is mean demand, T_t is a vector of unobservable time fixed effects, and ε_t is a serially correlated error term such that $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$ where u_t is random noise. The vector of unobservable time fixed effects T_t includes month fixed effects and day-of-week fixed effects to capture additional unobservable seasonality that is not captured by daily demand. It also includes a linear time trend variable, as well as year fixed effects to capture non-linear time trends. Both mean demand and intra-day demand volatility are assumed to be exogenous to price and intra-day price variance because of the focus on the wholesale market. As discussed in Section 2, retail consumers face no price pressures in the short term from the wholesale market because they are billed on a monthly level using a regulated rate instead of the average wholesale market rate. Instead, the primary drivers of daily demand are weather, season, and hour-of-day.

Since natural gas units are usually the marginal generating unit, they typically determine the marginal price of electricity in the wholesale market which also has implications for price variance. Thus, it is likely that natural gas capacity is endogenous with electricity price and intra-day price variance. To correct for the simultaneity bias, I use a two-stage least squares (2SLS) regression to instrument for natural gas capacity using a 31-day rolling average of the “spark spread”, lagged by 24 months. The spark spread is the gross margin between electricity price and the cost of generation using natural gas. More specifically,

$$SS_t = \sum_{i=0}^{30} \frac{1}{31} (p_{t-i} - NGP_{t-i} * HEAT_{t-i}) \quad (6)$$

where SS_t is the 31-day rolling average spark spread (\$USD/MWh) on day t , p_t is the daily average electricity spot price (\$USD/MWh), NGP_t is the natural gas price (\$USD/MMBtu), and $HEAT_t$ is the heat rate (MMBtu/MWh) which measures how efficiently a natural gas generator can convert gas into electricity. The spark spread gives a measure of the marginal profitability of generating electricity from natural gas and is highly relevant for investment decisions surrounding natural gas capacity. Further, a lagged spark spread is used as an instrument because it is intuitively correlated with future natural gas capacity, but is exogenous with respect to current prices. While some persistence in the spark spread may cause autocorrelation to remain at short intervals, at longer intervals this is shown to not be the case. Thus, a 24-month lag is used in the model. The long lag is due to a natural gas construction time of 18-36 months and should pass the exclusion restriction which requires the instrument to only influence current electricity prices through natural gas capacity.

5 Data

To test the role of natural gas capacity in the price stability of the wholesale electricity market, I use data from the Independent Systems Operator of New England (ISO-NE). Hourly electricity prices from the real-time ISO-NE market are obtained from March 2005 through June 2011. Throughout the analysis, prices and electricity demand loads are taken from the Southeast Massachusetts (SEMASS) zone, as it is geographically central to the ISO-NE. The data for both price and demand load are collapsed at the daily level to provide intra-day volatility for the 24-hour period.

Although “volatility” is colloquially used to imply “variability,” for clarity I define volatility as the standard deviation of the data.⁸ More formally:

$$\sigma_t^x = \sqrt{\frac{1}{24} \sum_{h=1}^{24} (x_{t,h} - \mu_t)^2} \quad (7)$$

where σ_t^x is intra-day volatility for the variable x on day t , h is the hour of day, and μ is the daily average of x . Thus, throughout the remainder of the analysis I use the terms “volatility” and standard deviation interchangeably.

Monthly summary statistics are shown in Table 3 for daily mean price, intra-day price volatility, daily mean demand, and intra-day demand volatility. The summary statistics are consistent with previous expectations about the New England electricity market, with the summer and winter months showing higher intra-day volatilities in addition to higher mean prices, mean-demands, and intra-day demand volatilities. The summary statistics suggest a strong seasonality to all variables of interest, which will be important to capture through month fixed effects. Lastly, the monthly summary statistics suggest findings consistent with the implications of the theoretical model in Section 3.

Figure 3 shows a clear relationship between intra-day price volatility and intra-day demand volatility. The graph uses a 60-day smoothing average to show general time trends without the daily statistical noise. The seasonality of intra-day demand volatility comes through very clearly, with a strong peak during the summer months and a second, smaller peak during early winter. An overall linear time trend is less obvious for either price or demand volatility, but there may be a slight decrease in both intra-day volatilities over time. Generally, periods of high demand volatility appear to coincide with high price volatility, a finding consistent with the intuition of the theoretical model in Section 3.

Figure 4 shows a similar trend, again with a clear seasonality for both daily mean demand and intra-day price volatility. The second peak during early winter is more pronounced in the mean demand graph than in the intra-day demand graph, but the two graphs are generally consistent with each other.

⁸This is also sometimes referred to as “historical volatility” in the finance literature, which is distinct from annualized volatility, implied volatility, variance, and the probability of extreme events.

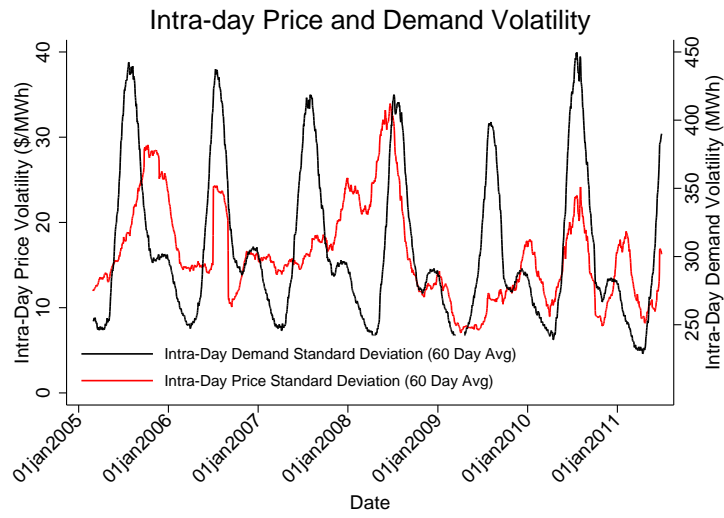


Figure 3: Intra-day Price and Demand Volatility

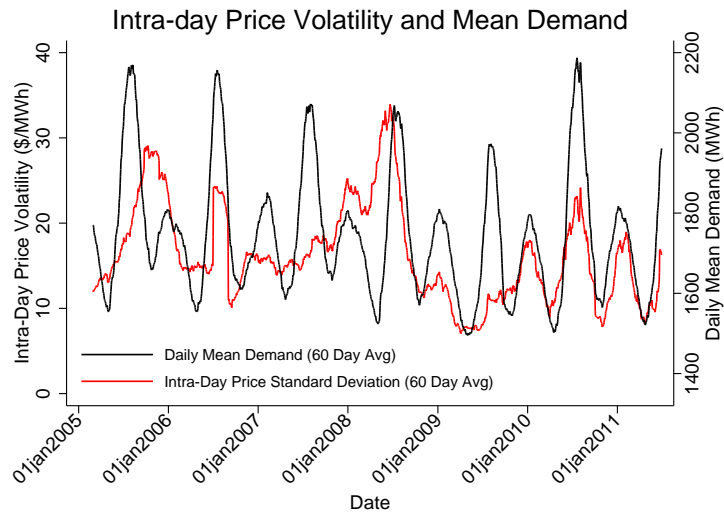


Figure 4: Intra-day Price Volatility and Mean Demand

Table 3: Summary Statistics for ISO-NE (March 2005 through June 2011)

Month	Obs (n)	Mean and Std. Dev. (in parentheses)			
		Daily Mean Price (\$USD/MWh)	Intra-Day Price Volatility (\$USD/MWh)	Daily Mean Demand (MWh)	Intra-Day Demand Volatility (MWh)
January	186	69.07 (21.42)	18.92 (10.35)	1,791.5 (107.0)	278.4 (33.6)
February	169	62.99 (16.81)	16.02 (8.13)	1,764.2 (108.1)	254.7 (33.5)
March	217	55.76 (16.74)	13.30 (7.58)	1,667.7 (118.4)	246.6 (43.0)
April	210	56.43 (20.71)	12.75 (8.25)	1,532.0 (91.3)	239.7 (37.3)
May	217	58.83 (23.99)	15.71 (11.42)	1,552.9 (113.7)	267.9 (47.4)
June	210	58.66 (25.37)	16.65 (12.58)	1,813.6 (246.3)	354.0 (91.1)
July	186	64.70 (26.90)	18.39 (11.84)	2,100.6 (284.2)	425.8 (99.7)
August	186	63.83 (27.30)	19.81 (30.82)	2,048.3 (284.4)	409.8 (100.6)
September	180	58.63 (24.94)	16.11 (11.69)	1,722.6 (197.3)	319.6 (67.6)
October	186	59.51 (26.68)	15.38 (13.38)	1,586.6 (100.3)	278.8 (36.6)
November	180	55.85 (15.02)	14.80 (8.23)	1,623.5 (86.6)	284.0 (32.2)
December	186	71.17 (24.15)	18.49 (9.11)	1,794.0 (116.4)	303.3 (38.2)
Total Sample	2313	61.11 (23.34)	16.28 (13.42)	1744.7 (242.2)	304.1 (84.5)

As implied by the basic and intuitive theoretical model, the temporal patterns of volatility and mean demand are highly correlated.

Data on natural gas generator heat rates and Massachusetts gas price are taken directly from the United States Energy Information Agency (EIA). Since heat rate data is provided by the EIA only at annual averages through their “Electric Power Annual Report” (EIA, 2013), a monthly rolling average is constructed which assumes linear technological improvements within the year. The EIA also provides monthly average natural gas prices paid by Massachusetts power plants using data from their “Monthly Cost and Quality of Fuels for Electric Plants Report” (form EIA-423) and “Power Plant Operations Report” (form EIA-923). The monthly data is then used to construct the marginal cost of electricity from natural gas, without considering operational expenses. Finally, a daily spark spread is constructed as the difference between the daily average electricity spot prices within the SEMASS zone and the marginal cost of electricity from natural gas.

Summary statistics for all variables used to construct the spark spread are shown in Table 4. As expected, the average heat rate improves over time from 9,207 Btu/kWh in 2003 to 8,159 Btu/kWh in

2009. Note that the heat rate data covers from March 2003 through June 2009, although the primary period of this analysis is from March 2005 through June 2011. This is because of the 24-month lagged spark spread used as the instrumental variable for natural gas capacity. Thus, the data from March 2003 through February 2005 is only used to calculate the instrumental variable and is not used as the dependent variable in the primary regression results of Section 6.

Table 4: Instrumental Variable Construction (March 2003 through June 2009)

Variable	Mean	Std. Dev.	Min	Max
Heat Rate (Btu/kWh)	8548	290.5	8159	9207
MA Gas Price (\$USD/1000 ft ³)	7.924	2.378	4.30	14.76
Electricity Cost from Gas (\$USD/MWh)	65.62	19.01	34.23	122.39
Daily Average Price (\$USD/MWh)	62.00	22.24	22.48	277.80
Spark Spread (\$USD/MWh)	-3.62	14.70	-62.07	210.73

The natural gas price paid by Massachusetts power plants during this period is \$7.9 per thousand cubic feet. This is expected, although it is slightly above the United States average of \$7.19 paid by power plants from March 2003 through June 2009. After calculating the marginal cost of electricity from the natural gas prices and the EIA average heat rates, the daily average is \$65.62 per megawatt-hour. As expected, this is very close to the mean spot price during this period (\$62/MWh) because natural gas generators are typically the marginal generator and thus set the electricity price. The difference between these leads to a small average spark spread of -\$3.62/MWh.

While a trivial average spark spread is expected it is also important to note the large variation. During the sample period, the daily average spark spread runs from -\$62/MWh to \$211/MWh. Further, many natural gas generators are “load following units” meaning that they ramp up generation to follow the increased demand during peak hours of the day when prices and demand are highest. The relatively low ramping costs of natural gas units means they can selectively operate during profitable hours. Thus, it is certainly possible to make a profit using natural gas generators even though the negative daily average spark spread initially suggests otherwise. Further, the 31-day rolling average spark spread that is used as an instrument smooths away from daily noise and remains a good measure of overall profitability for natural gas units. If the spark spread average remains high for some time, the increased profitability will induce additional entrants to build capacity. Thus, a positive spreads should encourage new investment in natural gas capacity.

Data on natural gas capacity is gathered from the EIA’s “Annual Electric Generator Report” (form EIA-860). The dataset includes generator level data for power plants in the United States and includes the state of operation, nameplate capacity, date placed in service, and date retired when it applies. Generator level data is collected for all states within the ISO-NE⁹ and changes in natural gas capacity

⁹As previously discussed in Section 2, this includes VT, CT, MA, ME, NH, & RI.

are constructed for 2005-2011 using installation and retirement dates. During this period total natural gas capacity in the EIA database increased by 730.1 MW, which amounts to just over 6% of installed natural gas capacity in 2010 (FERC, 2010). The additions came through nineteen new generators, with an average capacity of 60 MW each. These additions happened through thirteen new power plants, with an average capacity of 87 MW each. Further variations in total capacity come from the nine natural gas generator retirements, with an average capacity of 45 MW each. These capacity reductions happened through the closure of seven power plants, with an average capacity of 58 MW each.

While no new nuclear capacity has been installed or retired during the period studied, nuclear capacity occasionally goes offline for both planned and unplanned outages related to refueling, maintenance, and safety. Planned outages are typically scheduled months in advance and occur during regular refueling times and are generally considered exogenous, but the data is also analyzed using unplanned “forced outages” with no change to the results discussed in Section 6. Data on nuclear capacity outages within the ISO-NE comes directly from the US Nuclear Regulatory Commission’s “Power Reactor Status Report.” There are five active nuclear generators within the four nuclear power plants located inside the ISO-NE load area.¹⁰ The generators have an average capacity of 917 MW per generator, for total installed nuclear capacity of 4,586 MW. During the sample period, the average active installed capacity is 4,217 MW, such that active capacity was below installed capacity for 391 total days, or 17% of the sample. Included among these are 185 days from forced outages, or 8% of the total sample days. Since there are overlapping outages, perhaps a more insightful statistic during the sample period is an average outage time of 21.9 days per nuclear generator per year.

6 Results

The regression results for the two-stage least squares (2SLS) regression for natural gas capacity is provided in Table 6, with the first stage shown in Table 5. To correct for serial correlation of the error terms, Newey-West standard errors are reported in all specifications. The results are consistent with the intuition provided by the theoretical model in Section 3, with an increase in natural gas capacity showing a significant decrease in intra-day price volatility. Column (A) is the preferred specification, which includes controls for intra-day demand volatility, daily demand means, month fixed effects, year fixed effects, day-of-week fixed effects, and linear time trends. The results show that the marginal decrease in price volatility from adding an additional MW of natural gas capacity is \$0.028/MWh. Using the average 60 MW size of new natural gas capacity added in sample suggests that adding an additional natural gas

¹⁰The four power plants are Millstone Nuclear Power Station in Connecticut, Pilgrim Nuclear Generating Station in Massachusetts, Seabrook Nuclear Power Plant in New Hampshire, and Vermont Yankee Nuclear Power Plant in Vermont.

Table 5: First Stage 2SLS Results
Dependent Variable: Natural Gas Capacity (MW)

	(A)	(B)	(C)	(D)
Lagged Spark Spread (\$/MWh)	4.526*** (0.349)	6.147*** (0.539)	4.624*** (0.403)	4.219*** (0.432)
Time Fixed Effects	Yes	No	Yes	Yes
Kleibergen-Paap rk-statistic	167.87	129.67	131.21	95.14
Observations	2313	2313	2313	2313

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

Table 6: Second Stage 2SLS Results
Dependent Variable: Intra-day Price Volatility (\$/MWh)

	(A)	(B)	(C)	(D)
Natural Gas Capacity (MW)	-0.0278** (0.0109)	-0.0350*** (0.0075)	-0.0380*** (0.0123)	-0.0496*** (0.0146)
Demand Volatility (MWh)	0.0629*** (0.0068)	0.0391*** (0.0061)	0.0630*** (0.0069)	0.0632*** (0.0070)
Demand Mean (MWh)	0.0161*** (0.0026)	0.0103*** (0.0021)	0.0159*** (0.0026)	0.0157*** (0.0027)
Time Fixed Effects	Yes	No	Yes	Yes
Observations	2313	2313	2313	2313

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

generator decreases intra-day price volatility by about 10%, or \$1.66/MWh. This volatility decrease is approximately 2.7% of the mean electricity price during the sample period.

Column (A) of Table 6 also shows that intra-day price volatility significantly increases with both intra-demand volatility and mean demand, after considering seasonality and time trends. This is again consistent with the expectations of the theoretical model. Further, the marginal effect of an increase in demand volatility has a much larger effect than an increase in daily mean, as is intuitively expected.

The columns of the first stage regression in Table 5 coincide with the same columns of the second stage in Table 6. As expected, the lagged spark spread is strongly correlated with increases in natural gas capacity. In Column (A), the spark spread used is lagged two years and is a 31-day rolling average as discussed in Section 5. I also perform a weak instrument test using the rk-statistic of Kleibergen and Paap (2006) because the F-statistic of Cragg and Donald (1993) is not valid when the standard errors are not *i.i.d.* normal. Previous literature suggests a rule of thumb where there is little concern of a weak instrument with an F-statistic above 8.96 (Stock and Yogo, 2001, Stock et al., 2002). The preferred specification in Column (A) of Table 5 shows that the lagged spark spread is in fact a very strong instrument, with a Kleibergen-Paap rk-statistic of 167.87.

Column (B) of the regression results removes all of the time trend controls, but the marginal effect

of natural gas capacity is not significantly different from the previous column. There is a slight decrease in the marginal effects of demand volatility and mean demand, but they are still positive and significant as expected. The first stage results are qualitatively equivalent.

The regression results shown in Columns (C) and (D) add back in the time trend controls, but use a 60-day and 90-day rolling average for the lagged spark spread instead of a 31-day average. The results are not particularly sensitive to the number of days included in the rolling average of the spark spread. The marginal effects shown in Table 6 are not statistically different from Column (A), although they do increase slightly. Similarly, Table 5 shows that the instrument remains strong and yields no significant change in magnitude.

As discussed in Section 3, there are two effects of adding natural gas capacity. First, is the outward shift in the supply curve which should yield a decrease in intra-day price variance because demand intersects on a flatter convexity. The second effect, is the decrease in ramping costs which squeezes together the dynamic supply curve shifts, which also yields a decrease in intra-day price variance. The regression above captures both of these effects, but the ramping costs effect is of particular interest to this paper.

It may be possible to separate out these two effects using capacity changes that only affect volatility through outward supply curve shifts. For example, nuclear power faces relatively low marginal costs in addition to binding ramping constraints on the technology. For this reason, it is often used as a base-load power source and occupies the left most region of the supply curve in addition to renewable generators that have zero marginal cost. With this information it seems reasonable to assume that nuclear power outages will only shift the supply curve inward, without changing the intra-day dynamics involved from ramping costs. Thus, running the same specification on nuclear power should show changes in volatility due only to the supply curve shift.

As previously discussed, no new nuclear capacity has been built during the time period studied but outages do occur for refueling, planned maintenance, and occasional emergency shutdowns. The specifications shown in Table 7 use these temporary outages in nuclear capacity to understand the volatility changes from the supply shift. The results from an ordinary least squares (OLS) regression in Column (A) show a small but statistically significant decrease to price volatility from nuclear capacity. The marginal effect of an additional MW of nuclear capacity leads to a \$0.0013/MWh decrease in intra-day price volatility. Although nuclear outages are generally assumed to be exogenous, Column (B) uses an interaction effect between nuclear capacity and forced outages to ensure that forced outages behave similarly to planned outages. The results show that forced outages have a very small, insignificantly different effect on intra-day price volatility when compared to regular outages.

Column (C) of Table 7 includes natural gas capacity outages in the same regression, using the 2SLS

Table 7: Nuclear Outage Results
 Dependent Variable: Intra-day Price Volatility (\$/MWh)

	OLS (A)	OLS (B)	2SLS (C)	GARCH (D)	OLS (E)
Nuclear Capacity (MW)	-0.0013*** (0.0004)	-0.0014*** (0.0005)	-0.0027*** (0.0007)	-0.0012*** (0.0002)	-0.0019*** (0.0006)
Nuclear Capacity X Forced Outage (MW)		0.0001 (0.0004)	0.0002 (0.0004)		
Natural Gas Capacity (MW)			-0.0345*** (0.0119)	-0.0143*** (0.0017)	-0.0151** (0.0059)
Demand Volatility (MWh)	0.0626*** (0.0072)	0.0626*** (0.0072)	0.0633*** (0.0068)	0.0562*** (0.0035)	0.0628*** (0.0071)
Demand Mean (MWh)	0.0167** (0.0071)	0.0167** (0.0071)	0.0163*** (0.0026)	0.0149*** (0.0014)	0.0160** (0.0067)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	2313	2313	2313	2313	2313

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

specification to instrument for the natural gas capacity using the spark spread as discussed above. When including the capacities of both nuclear and natural gas power plants, the marginal effect of nuclear capacity on price volatility increases in magnitude to -0.0027. The interaction of nuclear capacity with forced outages again shows insignificant differences. Meanwhile, the marginal effect of natural gas capacity does not change significantly from the previously discussed regressions in Table 6.

Column (D) provides an alternative specification using the generalized autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev, 1987, Engle, 1982), which is sometimes used in the literature on electricity prices and volatilities (Hadsell et al., 2004, Worthington et al., 2005, Hadsell, 2007). In brief, the conditional intra-day volatility estimated by the GARCH model is

$$p_t = \phi + \varepsilon_t \quad (8)$$

$$v_t = \beta_0 + \beta_1 v_{t-1} + \beta_2 \varepsilon_{t-1} + \beta_3 NGC_t + \beta_4 S_t + \beta_5 D_t + \beta_6 T_t \quad (9)$$

where v_t is the intra-day price volatility (as measured through intra-day standard deviation) on day t , such that v_{t-1} represents the previous period's volatility forecast. Meanwhile, ε_{t-1} is a lagged error term representing new information about volatility from the previous period. Similar to prior equations, NGC_t is total natural gas capacity, S_t is intra-day demand volatility, D_t is mean demand, T_t is a vector of unobservable time fixed effects, p_t is electricity price, and ϕ is mean electricity price.

The results of the GARCH model in Column (D) of Table 7 are similar to the previous regressions, with an increase in natural gas capacity showing decreases to intra-day price volatility which are an order of magnitude greater than decreases from nuclear capacity. While the magnitude of the coefficient

on natural gas capacity is slightly lower than the preferred specification in Column (A) of Table 6, they are not statistically different. Further, the coefficient on nuclear capacity, mean demand, and demand volatility are also insignificantly different than prior specifications.

Lastly, Column (E) provides a pooled event study as an additional robustness check. In this specification, each natural gas capacity change is accompanied by a separate event window fixed effect in an OLS regression. The event window chosen for this analysis includes one month before and after the capacity change, and assumes the exact date of the capacity change is exogenous within this small window. As with previous specifications, the results suggest that the marginal decrease in volatility from natural gas capacity is an order of magnitude larger than that from nuclear capacity. Again, the coefficients on all regressors are insignificantly different from all prior specifications.

As discussed above, the discrepancies in the marginal effect between nuclear capacity and natural gas capacity are attributed to ramping costs. The results suggest that adding 60MW of nuclear capacity decreases intra-day price volatility by 0.5%, or \$0.084/MWh, while adding 60MW of natural gas capacity decreases intra-day price volatility by 10.2%, or \$1.668/MWh. Thus, empirically it appears that the reduction of volatility from the supply shift is actually quite small, although still statistically significant. The bulk of the volatility reduction comes through supply flexibility via decreased ramping costs. The results imply that adding 60 MW of natural gas capacity will decrease intra-day price volatility by 9.7 percentage points, or \$1.584/MWh, more than adding a lower marginal cost inflexible generator. This volatility reduction amounts to approximately 2.6% of the mean electricity price.

As an additional robustness check, I perform the identical analysis using an alternative measure of volatility that is also used in finance literature focused on electricity prices (Simonsen, 2005, Hadsell and Shawky, 2006, Zareipour et al., 2007, Ullrich, 2012, Haugom and Ullrich, 2012a). Here, the historical volatility is defined as the standard deviation of the logarithmic returns:

$$\sigma_t^r = \sqrt{\frac{1}{24} \sum_{h=1}^{24} (r_{t,h} - \bar{r}_t)^2} \quad (10)$$

where σ_t^r is the intra-day volatility of logarithmic returns on day t and h is the hour of day. Logarithmic returns are defined as

$$r_{t,h} = \ln \left(\frac{p_h}{p_{h-1}} \right) \quad (11)$$

where p_h is electricity price for hour h on day t .

Over the entire sample period, intra-day standard deviation of logarithmic returns is 0.2047 and the daily mean returns are close to zero, as expected, at -0.0040. While the intra-day volatility of returns is quite high, it is consistent with the range found in the previous literature which use this measure

Table 8: Second Stage 2SLS Alternative Results
Dependent Variable: Standard deviation of logarithmic returns

	(A)	(B)	(C)	(D)
Natural Gas Capacity (100 MW)	-0.0450*** (0.0164)	-0.0452*** (0.0108)	-0.0455** (0.0180)	0.0453** (0.0180)
Nuclear Capacity (100 MW)			-0.0002 (0.0010)	-0.0004 (0.0011)
Nuclear Capacity X Forced Outage (100 MW)				0.0003 (0.0007)
Time Fixed Effects	Yes	No	Yes	Yes
Observations	2313	2313	2313	2313
Kleibergen-Paap rk-statistic	167.86	129.68	148.82	150.05

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

(Zareipour et al., 2007).

The results are shown in Table 8 and are similar to the primary results. Adding natural gas capacity significantly reduces price volatility. Again, the coefficient on natural gas is an order of magnitude above the coefficient for nuclear capacity for all specifications. Across all specifications the coefficient for natural gas capacity are not significantly different from each other, while the coefficient on nuclear capacity is insignificantly different from zero. A 60 MW natural gas generator addition will decrease volatility by 0.027, or approximately 13%. This is only slightly above the results of previous tables estimates of approximately 10% when using a more traditional measure of volatility.

6.1 Consequences for Option Pricing

The reduction in daily volatility is especially important for risk averse power purchasers. Since electricity retailers face a fixed sale price to end users, they may hedge away from spot price risk through purchasing delivery contracts in the day-ahead market. The value of volatility reductions due to natural gas capacity can be captured through an option to buy electricity in a forward market. To quantify the value of such an option, I use the simple model developed by Black and Scholes (1973).

The Black-Scholes model provides a simple and common valuation of options, given a current asset price, exercise price, time to maturity, risk-free interest rate, and annualized volatility. I assume that one-year US Treasury bills are an appropriate proxy for the risk-free interest rate, as is common in asset valuation. Other assumptions include a one-day maturity time with no trading opportunities between days. It is reasonable to assume no trading opportunities between days because the electricity scheduled for delivery in hour h is a separate asset than electricity delivered in hour j , for all $h \neq j$. Thus, the annualized volatility input into the model is equivalent to the intra-day standard deviation of logarithmic returns in Section 6. Lastly, it is assumed that the option in question is equivalent to a

fixed price contract, hedging away from all price risk such that the daily mean electricity price is used for both the current asset price and the exercise price.

The described option is valued at \$0.237/MWh, which amounts to approximately 0.4% of the average daily price. Using the marginal effect from Section 6, adding a 60 MW natural gas generator will decrease volatility from 0.2047 to 0.1778. Thus, the price of the new option drops approximately 13% to \$0.206/MWh. The difference of \$0.031/MWh is interpreted as the market value of a volatility reduction from a 60 MW natural gas generator. While appearing as a small portion of electricity price, the ISO-NE transmitted 129,158 GWh in 2011 (ISO-NE, 2011). Thus, assuming power purchasers fully hedge away from spot price risk in the day-ahead market, the value of reduced volatility from a single 60 MW natural gas generator amounts to approximately \$4 million annually.

While \$4 million annual benefits appears small relative to the \$6.17 billion in 2011 electricity expenditures within the ISO-NE, a 60 MW generator represents only a small fraction of the 30 GW installed capacity within the ISO-NE region. In fact, the volatility reduction is quite large from a single generator, representing approximately 5% of its construction costs when using a \$1.2 million per MW basis seen in recent natural gas power plant construction costs (CPV, 2013).

The benefits described here accrue to power purchasers, but may not represent a dead weight loss because there is presumably a risk-neutral party profiting on the other side of the option. Instead, with the assumption that costs of electricity are fully passed from utilities to consumers, the annual benefits accrue to consumer surplus. Thus, a marginal increase of one 60 MW natural gas generator leads to a \$4 million annual increase in consumer surplus from the volatility reduction alone. This back of the envelope calculation does not consider additional externalities such as the value of added grid stability or the costs of pollution.

7 Natural Gas Capacity and the Forward Premium

Since adding flexible production capacity affects volatility in a similar fashion to electricity storage, there could be implications for the forward premium as well. Douglas and Popova (2008) argue that larger natural gas storage reserves lead to smaller forward premiums, as it is a form of indirect storage. As discussed in Section 1, their intuition is largely correct but their econometric model ignores the endogeneity concerns that can bias their results. In this section, I extend their regression analysis with a more rigorous empirical specification that specifically examines the effect of natural gas capacity on the forward premium.

Before starting the regression analysis, recall that the ex-ante forward premium is the difference

between the day-ahead price and the expected spot price:

$$PREM_t = FP_t - \mathbb{E}[SP_t] = FP_t - SP_t + u_t \quad (12)$$

where $PREM_t$ is the forward premium at time t , FP_t is the forward price, $\mathbb{E}[SP_t]$ is the expected spot price which is assumed equal to the actual spot price plus a random error term, u_t .

The seminal model by Bessembinder and Lemmon (2002) yields the testable hypothesis that the risk premium should be increasing with skewness of the price distribution and decreasing with the variance of the distribution. Since empirical investigations in the last decade have found mixed evidence in support of this notion (Longstaff and Wang, 2004, Douglas and Popova, 2008, Haugom and Ullrich, 2012b), it is worth exploring more in depth here.

The essential intuition is that the risk premium on forward contracts is lower in markets with lower ramping costs. This is because stored natural gas is equivalent to indirect storage of electricity. The lower ramping costs within new natural gas capacity should mean a greater ability to immediately convert the stored input into electricity. This increases the effectiveness of the indirect physical hedge which reduces the forward premium.

The reduced form econometric specification used in this analysis follows from the previous empirical literature (Longstaff and Wang, 2004, Douglas and Popova, 2008):

$$PREM_t = \beta_0 + \beta_1 NGC_t + \beta_2 VAR_{t-1} + \beta_3 SKEW_{t-1} + \varepsilon_t \quad (13)$$

where $PREM_t$ is the average hourly forward premium on day t , NGC_t is total natural gas capacity, VAR is variance of real-time price, $SKEW$ is the skewness of real-time price, and ε_t is a serially correlated error term such that $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$ where u_t is random noise. More specifically, a 7-day average of intra-day price variance is used for VAR as it arguably represents the best indication of ex-ante variance expectations. Similarly, a 7-day average of intra-day price skewness is used for $SKEW$. In all of the following results, the spark spread is used as an instrument for natural gas capacity via a 2SLS regression, as in Section 4.

The related regression results are presented in Table 9. Column (A) provides the most basic specification described above, which yields mixed evidence in support of the Bessembinder and Lemmon (2002) model and supporting literature (Longstaff and Wang, 2004, Douglas and Popova, 2008). Notably conflicting with the model is the coefficient on variance, which is essentially zero with a relatively small standard error. Meanwhile, the coefficient for skewness is positive and similar in magnitude to Longstaff and Wang (2004), although it is not statistically significant. Taken together, these coefficients

Table 9: Forward Premium Results: Second Stage 2SLS
 Dependent Variable: Standard deviation of logarithmic returns

	(A)	(B)	(C)
Natural Gas Capacity (MW)	-0.0183*** (0.0068)	-0.0246** (0.0104)	-0.0241** (0.0105)
Variance (MW)	0.0000 (0.0002)	-0.0000 (0.0002)	-0.0000 (0.0002)
Skewness (MW)	0.2030 (0.5304)	0.4608 (0.5047)	0.4728 (0.5067)
Demand (MW)	0.0020* (0.0013)	0.0016 (0.0013)	0.0016 (0.0013)
Year Fixed Effects	No	Yes	Yes
Linear Time Trend	No	No	Yes
Observations	2313	2313	2313
Kleibergen-Paap rk-statistic	104.15	140.75	139.77

Note: ***, **, & * denote statistical significance at the 1%, 5%, and 10% levels respectively. Newey-West standard errors are reported in parenthesis to correct for serial correlation.

are more supportive of recent literature by Haugom and Ullrich (2012*b*) instead, which argues that more recent data does not support the Bessembinder and Lemmon (2002) model. However, as predicted by Bessembinder and Lemmon (2002), the forward premium increases with demand in my analysis as well. This finding coincides with Douglas and Popova (2008) who use weather variables as a proxy for demand. As might be expected, this effect loses significance in Column (B) and Column (C) because the time trends remove a lot of the long run variation in demand.

Most interesting is the expected results that show the risk premium decreasing significantly with increases in natural gas capacity. The results in Column (A) suggest that each additional MW of natural gas capacity decrease the forward premium by \$0.018, or about 3% of the average forward premium during the sample period. Columns (B) and (C) add year fixed effects and linear time trends, but see no significant difference in the marginal effect of natural gas capacity on the forward premium.

A persistent forward premium implies that there is some risk premium in buying forward price contracts, such that the risk aversion of power purchasers dominates that of electricity generators. Thus, I interpret these results as evidence that additional natural gas capacity reduces demand for forward contracts because of their low ramping costs. Lower ramping costs imply less price risk in the spot market. In other words, markets with a larger share of natural gas generators require a smaller forward premium on price contracts in the day-ahead market because natural gas generators provide an indirect physical hedge in place of an option that provides a direct financial hedge.

8 Conclusions

The indirect impacts of additional natural gas capacity on wholesale electricity market price behavior have not been fully analyzed in the previous literature. While natural gas capacity has obvious effects on the mean price of electricity, there is minimal discussion on the implications for price volatility. The ramping ability of natural gas plants is particularly important since there is not yet an efficient market for ramping ability within the FERC's "Standard Market Design" (Stoft, 2002, Wang and Hobbs, 2014). My analysis provides several contributions to the existing literature on electricity markets, as it describes and quantifies the additional benefits from adding flexible generation capacity. First, it formalizes the intuitive link between natural gas capacity and price volatility due to ramping costs. Second, it implements a rigorous empirical analysis which provides supporting evidence to the theoretical model. Finally, it builds on previous literature connecting natural gas markets and the forward premium in electricity markets, while adding to the debate over the Bessembinder and Lemmon (2002) model.

In this paper I develop a basic theoretical model which details the importance of ramping costs on electricity market price volatility. In the absence of cost-effective storage, ramping costs are a major contributor to price volatility in the electricity market. The model shows that adding generation capacity with lower ramping costs and lower marginal costs will unambiguously decrease intra-day price volatility under the standard assumptions of convexity in the cost curve. Further, the implications of the model easily generalize to all non-storable, or perishable, commodities where there are marginal costs of adjusting output. In brief, flexible production can serve a similar role to storage in ensuring price stability.

A reduced form econometric specification is inferred from the equilibrium conditions of the model and the empirical evidence supports the theory. More specifically, using a 2SLS regression to instrument for endogeneity, I find that a 60 MW natural gas generator will reduce price volatility by approximately 10% in the wholesale market. These results are robust to various instrument constructions, a pooled event study analysis, and a generalized autoregressive conditional heteroskedasticity (GARCH) model. This translates to a \$4 million annual gain in consumer surplus due to the lower options price resulting from decreasing price volatility.

The econometric analysis also shows additional natural gas capacity decreasing the forward premium, extending the previous literature (Routledge et al., 2001, Bessembinder and Lemmon, 2002, Longstaff and Wang, 2004, Ullrich, 2007, Douglas and Popova, 2008, Huisman and Kilic, 2010). In an efficient market with risk-neutral traders the forward premium should converge to zero (Jha and Wolak, 2013), so natural gas capacity additions arguably increase the overall efficiency of ISO-NE market.

Taken together, the results of this analysis point electricity market regulators towards specific policies.

First, market design and policies should acknowledge that there are additional benefits around adding capacity that has both low ramping costs and low marginal costs, such as natural gas generators. This is increasingly important when considering the future growth of non-dispatchable generators such as wind and solar. Since the benefits around ramping costs are not currently priced under the current design of electricity markets, incentives must be created to ensure such benefits are internalized into long-run capital investment decisions. This can be done through an additional market for ramping services, as several transmission organizations have begun to discuss (Wang and Hobbs, 2014). In the meantime, construction subsidies may be offered to ensure additional investment in flexible generators. Incentive-based support mechanisms should remain in place until cost-effective storage reduces ramping issues to irrelevance.

Future research will consider the effect of natural gas capacity on price volatility and the forward premium during different time intervals. For example, it could be that intra-day volatility is decreasing due to natural gas generators but at longer monthly intervals these volatility benefits attenuate, or even reverse. This possibility is allowed because over longer time horizons, natural gas generators are subject to fossil fuel price volatility. Meanwhile, future research on the forward premium will focus on the effect of natural gas capacity on each specific hourly premium to better understand which hours are driving the result.

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